The nature, causes and consequences of financial analysts' forecasts in the UK

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Abstract

This thesis consists of three empirical chapters that investigate the nature, reasons and consequences of financial analysts' forecasts in London Stock Exchange. The first empirical chapter examines the rationality and accuracy of financial analysts' forecasts. Results show that analyst forecasts are overall optimistic, but not as extreme as the literature suggests. However, analysts seem to converge to a more rational position the closer they get to the announcement date. Despite no evidence of relationship is found between forecast error and prior year change in earnings per share, analysts are believed to be systematically revising their forecasts downwards as the time approaches the earnings' announcement date. The second empirical chapter attempts to study the factors that contribute to the forecast error and in particular earnings management. Results show that earnings management positively affects the magnitude of the forecast error, that is, when earnings are manipulated the forecast error appears to be bigger. However, this positive impact appears to be driven by accruals earnings management and not by real earnings management. Moreover, forecasts seem to be more optimistic for companies that manage their earnings downwards through accruals. These findings reveal that analysts may not be as biased as the literature claim, instead, they are probably victims of earnings management. The third empirical chapter examines whether financial analysts' forecast is a major component of market sentiment and tests how this contribution can affect cross sectional returns. Results confirm that analysts releasing higher than average earnings per share forecasts lead to higher sentiment levels. Inconsistent with previous literature, short term stock returns are significantly positively affected by sentiment levels, but growth stocks appear to be more sensitive to shifts in sentiment than value stocks.

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Chapter 1: Introduction:

1.2. Introduction

The rise of finance in modern history mirrors a dominant era of financial markets on the global economy. The scope of economic and financial interactions between the different countries and corporations is simply impossible to imagine without the existence of financial markets. At the heart of these financial markets sits financial analysts. Many people look at financial analysts as the “greedy whipping boys” who earn an unbelievable amount of money while sitting for few a hours in some skyscraper’s office. The latest financial crisis added even more resentment towards financial institutions including financial analysts, as they were seen the main reason behind 2008 financial crisis. Nevertheless, who are financial analysts? And what role do they play in the financial markets?

Contrary to peoples’ belief, financial analyst’s career is among the most rigorous yet rewarding jobs in the market. Early career analysts are expected to spend the majority of the time in gathering data from news, analyse reports and industry publications in order to develop a fundamental understanding of a particular business or industry sector. After achieving a certain level of knowledge as well as a good network of market contacts, financial analysts are supposed to put their expertise and turn their numbers into forecasting future performances and investment recommendations. While doing so, they must acquire a strong marketing ability to sell their opinions thus convince others (mainly investors) that not just their numbers are accurate, but what lies behind their figures is concrete.

The life of a financial analyst is rather challenging and rewarding, however, it comes at a big cost. According to The Job Crowd database, the average working hours of a junior financial analyst is 12 hours a day, which is 4 hours more than the average full time employee in other industries. In September 2011, Joris Luyendijk wrote on “Voices of Finance” in “The Guardian” about the life of a previous financial analyst at a major bank. The analyst reports that working as a junior in a city corporation is insanely demanding, to the point that you would dream of having free weekends at most of the times, and that money cannot comensate for the tough life style expected from an analyst (The Guardian, 2011).

One of the main roles that analysts do is forecasting company's earnings. Analysts' consensus earnings' forecasts are used by the market to judge the performance of companies. Backed by their fundamental analysis as well as current news, analysts produce earnings' forecasts at different stages throughout the fiscal year and some may revise their forecasts at later stages. These forecasts constitute a main source of information for investors to make their investment decisions. The implication of analysts' forecast go beyond just being a source of information investors take into consideration. How accurate these forecasts are and what direction they take could result in serious consequences on the financial market. Along with the media, these forecasts will create a market expectation regarding a certain stock which will lead to a strong reaction if these expectations are not met, and the higher the error made by analysts the stronger the reaction of the market. In 2010, for example, consensus analysts polled on Thomson Reuters forecasted the revenue of Palm (a former smartphone maker), to be $1.6 billion for the full fiscal year (CNN, 2010). Although revenues for that year were already low compared to Palm's usual performance, the company announced that their revenues would be way below the market expectation ($285 million). This news came as a shock and market prices plunged by almost 30%. As negative news regarding Palm's future kept on showing, some analysts even estimated the share price to be valued at $0, recommending investors to sell their Palm's share. Much to their disbelief, Hewlett-Packard offered to acquire Palm for $5.7 a share when it was trading at $4, keeping investors that listened to the $0 valuation in shock.

While many acknowledges the professionalism of analysts and their expertise in the field, they are human beings and are subject to committing errors when forecasting a company's performance. In this manner, most studies show that analysts' forecasts are overall optimistic regarding company's earnings (Easterwood and Nutt (1999), Ciconne (2005). Other studies go even further and claim that analysts' forecasts are not just optimistic but also extreme which makes their rationality questionable (DeBondt and Thaler (1990) and Capstaff et al (2001)). There exists, indeed, other cases in which analysts were seen pessimistic. Henderson and Marks (2013) for example report that analysts are overall pessimistic when it comes to forecasting revenues and earnings.

Taking the debate around analyst forecast error a step further, many academics questioned the reliability and efficiency of analysts after they observed trends in their forecasts. A popular trend is when some analysts systematically revise their earnings forecast downwards on many occasions during the fiscal year. In particular, this downward revision is mainly observed towards the end of the fiscal year. This has been statistically proven by Debondt and Thaler (1990), Capstaff et. al (1995) and Capstaff et. al (2001)) and many more.

From extremely optimistic to downward revisions, these biases of earnings forecasts are not caused randomly but through clear motivations that led forecasters to deliberately commit some direction in their forecasts. One important reason behind optimistic forecasts is based on the sell-side theory, in which sell-side analysts tend to release favourable results that push for more investments. McNichols and O'Brien (1997) denote that even when analysts are not biased, we still see optimistic forecasts, as analysts prefer not to release unfavourable forecasts in most of the cases. Another important motivation is the relationship between managers and analysts. At the beginning of the fiscal year, analysts tend to release optimistic forecasts in order to stimulate stock prices. However, as time approaches the of fiscal year, analysts lower their forecasts gradually allowing the reported earnings to meet or beat these forecasts. These forecast revisions would lead to a positive earnings surprise that appears in favour of the managers. In return, this theory assumes that analysts follow such trend hoping to preserve private access to companies' managers. The supporters of this theory are many including Mest and Plummer (2003) and Das, Levine and Sivaramaknishnan (1998), Richardson, Teoh and Wysocki (2004), and Baron, Biard and Liang (2013). Based on this theory, Baron et al. (2013) investigate the timing in the year at which analyst forecasts are released compared to their type. They find that on average, pessimistic forecasts are issued later in the year than optimistic ones, which may explain why the last quarter of a fiscal year is less optimistic in terms of earnings forecast. Additionally, their main argument is that why would analysts holding unfavourable forecast figures release them later in the year, unless they tend to help managers to reach a positive earnings surprise. They also find a positive and statistically significant relationship between optimistic forecasts and trading volumes. Notwithstanding, having trends in analyst forecasts at some point does not mean that all analysts are biased. The reason for this claim is that trends can be generated from different sources and reasons. To be more specific, when analysts' forecast show a downward revision trend, it might be due to them acquiring more information about the company all along the fiscal year which helps them to be more accurate in their forecast analysis. Having said that, there exists no clear-cut evidence that managers talk down analysts' forecasts in order to meet or beat public expectation and reach a positive surprise. It is very important to note that these are only suggestions that came up after examining the motivations of market participants which has led to that specific reasoning.

All things considered, this research investigates analysts' forecasts concerning the UK companies from an objective point of view. While it follows the literature to some extent in order to examine all possible factors surrounding analysts' earnings forecast, it contributes by revising some of these theories and provide statistical evidence to show how analysts' forecasts should be observed from a different scope. Motivated by the importance of analyst forecasts in financial markets, this research provides three empirical chapters that examines the accuracy of these forecasts on aggregate, what factors can cause analysts' forecast errors to increase, and finally the consequences of these errors. These three chapters complete each other in the way that the models chosen for each of them analyse the issues from different angles. The standpoint in chapter 2 is to critically assess the accuracy and rationality of financial analysts. Chapter 3, however, assumes that forecast error cannot be based on biased forecasts solely, as other external factors might cause this error to increase. Albeit different motivations and reasons stand behind the forecast error, one can admit that this error can have an impact on the financial market. Chapter 4 addresses this issue and examines the effect of forecast error on stock returns.

To start with, the first empirical chapter in this research talks about the overall accuracy of analyst earnings forecasts. While doing so, it breaks down analyst forecast accuracy into two categories. The first is simply how far is the aggregate earnings' forecast from the reported earnings per share, the second observes whether the forecast falls below the reported earnings per share (pessimistic forecast) or above the earnings per share (optimistic forecast). The study in the first empirical chapter covers all companies listed in FTSE All Share index (Financial Times Stock Exchange) in London Stock Exchange for a period starting from 1993 until 2013. The main reason for starting from 1993 is to make sure that companies have adopted the third Financial Reporting Standard FRS3 into their reports[1]. The companies are selected according to each year's true number of available public companies at the time of the observation year.

Moreover, the first empirical chapter attempts to fill many gaps in the literature that covered a similar topic. To our knowledge, all findings provided in previous studies show weaknesses in their data management[2], which might have led to unreliable results instead being statistically singnificant. A critical review of these gaps and ways to correct for them are discussed thoroughly. With a better organised and more suited sample, this research attempts to re-examine the analyst forecast rationality and bias, by providing insight information about the forecast error month by month until the earnings announcement date. Additionally, the first empirical chapter investigates the rationality of analyst forecasts by testing some popular trends including the downward revision trend following Debondt and Thaler (1990) and Capstaff et al. (2001) and whether financial analysts incorporate companies' past earnings in their financial forecasts following Abarbanell and Lehavy (1992).

The importance of the first empirical chapter lies in understanding the characteristics of analyst forecasts regarding the UK companies as well as proving empirically how these forecasts are directed and whether they are optimistic or pessimistic in their figures. Another essential part is to observe the evolution of financial analysts' forecasts over 20 years, and compare the findings with previous related studies that covered different periods for UK companies. As discussed earlier, this chapter tries to uncover the bias in earnings forecasts as they are seen through the statistical evidence, and although it links the findings to the theories provided in the literature, chapter 2 leaves a margin for other factors to be addressed in the following chapters.
The second empirical chapter focuses on the variables that affect analysts' forecast error. The chapter highlights how difficult it is for analysts to forecast a company's earnings, as it involves conducting a fundamental analysis based on available information and news that

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[1] A detailed discussion on the changes in the accounting standards and its impact on the forecasts is provided in the first empirical chapter

[2] Types of shortcomings include observing forecasts until the fiscal year end only, assuming all companies release their annual reports after a fixed number of months of the fiscal year end, using a fixed number of companies throughout the overall period of study (called the survivorship effect) and many more. These pitfalls will be discussed in details in the first empirical chapter.

are continually released, and possibly missing on many unobserved variables. A very important factor that analysts might find hard to observe is earnings management. Earnings management is the procedure of managing the discretionary variables that affect the bottom line of the income statement. This could be done via two main categories: accruals-based earnings management and real earnings management. Accruals-earnings management is an accounting management tool that alters the estimated accruals accounts in order to boost or decrease the company's earnings. Real earnings management is when managers adjust the short-term real activities expenditures, such as Research and Developments or Advertisement, in order to reshape the earnings. Earnings management is a popular tool that managers use for many reasons. The most reasonable motivation is boosting earnings in the short term in order to avoid losses (Roychowdhury (2008), Burrgstahler and Dichev (1997)), and short-term earnings management provides a quick solution for it. Another reason is that managers would defer their earnings at some point in anticipation of dry future periods, which will smooth out the volatility in earnings (DeAngelo et al. (1996)). This method would make earnings look more stable and show the company's weaknesses in certain periods. Perhaps the most sensitive motivation discussed in the literature is the relationship between manager's compensation and earnings management. Some studies show that earnings related compensations and the bonus schemes are the main motivation as to why managers tend to use this tool to boost earnings (Healy (1985), Bergstresser and Philippon (2006)).

Based on the above documentation, it is commonly assumed that many managers use earnings management as a tool to help them reach one of the above motivations. Applying such adjustments is managed internally with information surrounding such alteration becomes of a speculative nature. Assuming there is no possibility for information leakage, there is no doubt that earnings management would make the forecasters job even harder leading to a higher forecast error as reported earnings show up differently to what they were initially anticipated.

Consequently, this chapter tries to empirically test whether earnings management holds a causal effect on forecast error. The models used include other probably influencing variables such as the number of analysts following a company, firm's profitability in previous years, trading volume of the related stock, the level of earnings' uncertainty and other controlling variables.

Another motivation behind earnings management is that managers try to meet or beat analysts' forecasts in order to generate a positive surprise (Libby et al. (2007), Ke and Yu (2006), Bernhardt and Campello (2007)). If this is true, forecast error and earnings management might bear a reversal causality. For this reason, chapter 3 controls for this issue by creating a sample of suspicious and unsuspicious forecasts then runs different tests on each. Moreover, the analysis employs the "Generalised methods of moments" (GMM) in order to control for a possible endogeneity problem.

The second empirical chapter contributes to the literature by providing an empirical evidence of the negative effect caused by earnings management. While chapter 2 shows that analysts' forecasts appear to be generally optimistic, the second chapter claims that analysts are not alone guilty of their forecast optimism, and that earnings management could be one of the reasons why these forecasts appear to be inaccurate or even showing possible abnormal trends.

After discussing the nature and characteristics of forecasts in chapter 2 and the external variables that might contribute to this error in chapter 3, one evident truth remains unchanged is that the forecast error will have a serious impact on the stock market due to the major role financial analysts play.

Therefore, the third empirical chapter pursues the consequences of analysts' forecast error and attempts to find an answer of the impact of forecast errors can have on the financial markets. Previous studies suggest that drifts in prices that occur straight after the earnings are announced, are partially driven by analysts' earnings forecasts which feed the market with earnings expectations during the period before the announcement date (Abarbanel and Bernard (1992), Lundholm and Soliman (2006)). As a result, the drift in prices is a natural reaction of the market. The same findings had initially been proven by Watts (1978). Others claim that firms that meet or beat consensus earnings forecasts report higher stock returns than the ones that don't (Bartov et al. (2002), Bernhard and Campello (2007)).

Many of these findings touch on the existence of a behavioural aspect in analysts forecast. According to DeBondt and Thaler (1990), earnings forecasts are too extreme to be rational and analysts overreact to previous information. Concerning the stock market, the authors add that there exist many reasons to believe that investors are subject to the same cognitive biases as any human being. Based on these arguments, a behavioural common factor appears to be shared between financial analysts and investors. This leads us to Market Sentiment. On the one side, Brown and Cliff (2004) define Market Sentiment as expectation of market participants relative to a norm, which is the average return. On the other side, analyst forecasts logically contribute to the market expectation via releasing performance predictions relative to a norm.

Market sentiment is proven to be directly related to stock returns in many financial markets but the literature shows contradicting results. Baker and wurgler (2006) show that when sentiment is low, subsequent stock return appear to be high on the long horizon for small and vulnerable stocks. Moreover, Schmelling (2009) also find a negative relationship between sentiment levels and future returns. Results shown by Fisher and Statman (2006), however, suggest a positive relationship between individual investors's sentiment and returns on small stocks. Scheinkman and Xiong (2003) claim that market sentiment play an important role in creating a market bubbles.

Consequently, chapter 4 suggests that the impact of forecast error on cross-sectional stock returns exists via its contribution to the Market Sentiment, and not as a direct measure. Therefore, the chapter sees forecast optimism as a component of Market sentiment and expects their relationship to be positive. Following Baker and Wurgler (2006), a sentiment index is estimated based on the principal component analysis of seven factors that come as follow: Analyst forecast error, the dividend premium, the return on IPOs, the number of IPOs, the share of equity issues over total issues, share turnover ratio and discount on closed end fund. After the construction of the sentiment index, the analysis of this chapter examines the impact of market sentiment on stock returns depending on detailed stock portfolios based on Fama and French (2014) five factors. This research provides a detailed comparison of stock returns during periods of high and low sentiment levels. Moreover, it attempts to investigate the value premium puzzle by comparing how returns on growth or value stocks change from one sentiment level to another.

The third empirical chapter contributes to the literature in many ways. First, it introduces a new measure of Market Sentiment by considering analysts forecast error as a major component. To our knowledge, previous studies attempt to see the reaction of the stock market using long horizons, however, this research believes that the information and news in the market are absorbed and reflected very quickly in the stocks. Therefore, the second contribution would be by examining the short term monthly impact of sentiment on stock returns. Third, it will particularly address the relationship between investor sentiment and the value premium pattern. While doing so, it helps unlocking this puzzle by introducing the forecast error as a component of market sentiment.

The remainder of the research will come as follow: the next section discusses the research background and rationale of the thesis. Section 1.4 discusses the research questions with a brief outline of the findings. The following section explains the reasons for choosing the UK market as a sample study and highlight the key characteristics of London Stock Exchange. The last section in the Introduction chapter talks about the research philosophy. Following the research philosophy section, there are three empirical chapters. Chapter 2 examines the nature, accuracy and rationality of analyst forecasts. Chapter 3 studies the external reasons that contribute to the forecast error in particular earnings management. Chapter 4 investigates the impact of forecast error on stock returns using Market Sentiment as an intermediary. The last section concludes.

1.3. Research Background and Rationale:

Considering the importance of financial analysts in the market, this thesis puts analysts' forecasts as the focal point for investigation. A great deal of the literature examines forecasts' accuracy and rationality in a rather exploratory manner and show that consensus forecasts are overall optimistic and are not rational (DeBondt and Thaler (1990), Easterwood and Nutt (1999)).

However, looking at analysts' performance alone would only explain one side of the story. Analysts are surrounded and affected by all sorts of market factors, thus one should be very careful when making a judgement regarding their performance and whatever is attributed to it. For sure academic articles encounter some restrictions regarding the time and size of the research conducted, and this is why a doctorate study such as this, can add value to the literature by providing a comprehensive research about financial analysts' forecast.

1.3.1. Financial analysts' performance and rationality:

The academic field started to show some interest in financial analysts after 1975. Gillis (1975) for example, proposes some important points that must be considered when forecasting a company's performance and those include general and economic factors, industry factors and firm specific factors. According to the author, any divergence from the value of these factors will increase the forecast error. In an empirical study, Patz (1989) evaluates analysts' forecast accuracy for the UK firms depending on few characteristics such as size and industry. Findings show that large companies appear to have better forecast accuracy, and this is mainly due to the bigger attention they receive and more information available about them. The author's findings also suggest that analysts are considered accurate if their forecasts are made for 12 months ahead at most. For longer targets, analysts' accuracy start to deteriorate. The author also finds that industry matters a lot when it comes to large forecast errors, suggesting that industry categories must be taken into consideration as a control variable. The reason for this is that analysts' might be specialised in some industries and not others, which will make the sample biased if some consensus observations are made of very few forecasts. Another study that evaluates the performance of analysts' forecasts is Fried and Givoly (1982). According to Fried and Givoly (1982) analysts' forecasts are better proxies of market prices than time series models. This is due to the flexibility of analysts to incorporate a large set of information and the timing advantage that they have in forecasting even after the end of fiscal year.

Despite the superiority of analysts' forecasts over time series models, they are found to be optimistic in most of the studies. DeBondt and Thaler (1990) document that analysts are not just optimistic, but also extreme in their predictions. The authors also show that anlaysts are irrational as they show a systematic trend in their revisions. The latter was attributed to behavioural reasons. Rationality of forecasts imply that analysts react efficiently and quickly to new information and incorporate it in their analysis. This type of rationality is investigated by Easterwood and Nutt (1999) who study the reaction of analysts depending on the nature of information they receive. They find that on average, analysts underreact to negative news and overreact to positive ones. Similar to DeBondt and Thaler (1990), Easterwood and Nutt (1999) concludes that analysts are irrational when it comes to reflecting information in their forecasts. Moreover, this is consistent with systematic optimism in responding to new information.

Furthermore, analysts' forecasts seem to vary depending on firm-specific variables such as last year's performance. Ciconne (2005) claims that loss firms are different than profit firms specially when it comes to forecasting. In a sample of 120,022 firms-quarter, Ciconne (2005) finds that firms that announce losses in a specific year become harder to forecast during the following year. Contrarily, analysts' forecasts appear to be smaller for firms announcing profits. The relationship between firms specific characteristics and analysts' forecast is also studied by Coen et al. (2009) who find that forecast error is higher for companies that either announce losses or show a decrease in their previous earnings.

They also find that the consensus forecast error decreases as the number of analysts following a certain company increases.

Henderson and marks (2013) suggests that earnings per share forecasts is not the best variable to use in order to judge the performance of the analyst. They suggest that profit margin is a better proxy and should be used instead as it incorporates revenues which is a reference point of the company's performance. Contrary to the overall literature, they find that earnings and revenue forecasts are overall pessimistic. Furthermore, Baron, Biard and Liang (2013) observe the time at which forecasts were made and find that pessimistic forecasts are often issued later in the year compared to optimistic forecasts that are issued earlier in the year.

Back to the rationality of analysts, the literature also shows big interest in the relationship between financial anaylsts and companies' managers. A big question mark is raised when linking analysts' forecasts with company's performance. Das, Levine and Sivaramaknishnan (1998) for example, suggests that analysts might issue biased forecasts to gain access to private information from managers of hardly predictable companies. Their analysis confirms that analysts are significantly optimistic when forecasting hard to predict companies. This is consistent with Mest and Plummer (2003) who suggests that optimism in earnings forecasts can improve access to management, thus if managers give less attention to forecasts, intentional bias in earnings forecasts decreases and become more accurate. They prove their hypothesis by showing that optimism in earnings forecasts is significantly greater than sales forecasts. Libby et al. (2007) state that not only analysts have an advantage in having a good relationship with managers, managers may indirectly use analysts to their own favour by forcing them to issue favourable forecasts regarding their company. This could explain why a lot of analysts issue optimistic forecasts early in the year but lower their forecasts using later revisions to allow managers to meet or beat the expectation. The motivation behind this is explained by Bernhardt and Campello (2007) who report that firms might, on purpose, generate earnings that exceed analysts' forecasts in order to make a positive surprise and stimulate the stock price after the earnings announcement. Using quarterly data for a sample between 1989 and 1999, they find that forecasts issued later in the fiscal year have bigger impact on investment decisions compared to the early ones. More precisely, stocks earn 69% higher return after earnings announcement when the actual earnings meet the latest forecasts, compared to companies' stocks that don't meet or beat earnings' forecasts.

Nevertheless, gaps in the literature concerning the samples selected and the way the data has been managed raises a lot of questions to whether the analysts are excessively optimistic as the literature suggests or not. One of these weaknesses is to observe the analysts' earnings forecasts only until the end of the fiscal year. Das et al. (1998), Eams and Glover (2003), Easterwood and Nutt (1999) all follow this criterion when they analyse the accuracy of financial analysts. According to the FCA (Financial conduct authority) in the UK, listed companies are allowed to publish their annual report and financial statements until 120 days after the fiscal year end. Moreover, there exists no company at all that publishes its accounts in the same month of the fiscal year end. Additionally, analysts continue to forecast companies' earnings until the announcement date and not until the companies close their books. This is very important as forecasters tend to be more accurate by the end of the period as more information emerges regarding the underlying companies.

Other articles applied some slightly different criteria to the forecasting horizon. Capstaff et al. (2001) for example assumes that companies publish their results within 3 months, therefore, they set the forecasting window from three months after the previous fiscal year end to three months after the current fiscal year end. However, the time taken from the fiscal year end until the announcement date is different between companies (chapter 2 provides full details regarding FTSE all share companies). Similar pitfalls include taking companies with fiscal year ending in December only (Larocque (2013), Becker et al (2004), among others), or studying a fixed number of public companies surviving over a long period in time (Guedj and Bouchaud (2005). Such misalignment can have serious implications on the results provided and may not truly represent how accurate these forecasts are, leave aside their bias or rationality. Consequently, this thesis will attempt to re-examine the financial analysts' accuracy and rationality after covering the gaps in the literature by providing a detailed representation and a well organised sample data for FTSE all share companies in the UK.

1.3.2. Companies' managers versus financial analysts:

As for the managers, their role surpasses putting pressure on analysts, but it also consists of managing their own earnings and improve their companies' performance, or at least, improve it in the eyes of the public. Therefore, it is essential to discuss the role of managers and earnings management in this theme to better understand earnings' forecast error.

Earnings management is one of the most popular tools in accounting management. It is the procedure of reshaping the accounting figures, especially the discretionary accounts, in order to improve the end of year earnings. From the accruals' perspective, this could be done by recognising sales not yet delivered, changing inventory methods, timing gains and losses and many more. From a real activities' perspective, managers can cut expenses of advertisement and research and development, offer lenient credit terms to boost sales in the short term, overproduce units to lower the unit cost.

There exists a lot of incentives that stand behind earnings management. The most obvious reason is to boost earnings and meet public expectations (Burgstahler and Eams (2006), Carmanis and Lennox (2008), Bernhardt and Campello (2007), among others). As stated earlier, Bernhardt and Campello (2007) documents how meeting public expectation can increase stock returns following earnings announcement. Others claim that avoiding losses is a benchmark for managers thus it is the main incentive behind using earnings management (Roychowdhury (2006)).

Managers are also believed to be driven by financial bonuses. Bergstresser and Philippon (2006) shows that insider ownership is highly correlated with earnings management. They find that CEOs are more likely to exercise options in periods of high accruals. Kraft, Lee and Lapotta (2014) insider shares trading increases following periods of high accruals. As such, this finding is based on a simple assumption that manager's wealth is associated with company's performance.

Perhaps this could be more evident when we compare earnings management with manager's bonus schemes. Fox (1980) reports that 90% of the largest US companies apply earnings based bonus plans. Based on this, Healy (1985) observes how companies' accounting procedures change when the bonus plans are modified. The author then argues that managers manage their discretionary accounts in the optimal way that maximises their utility from bonus awards. Financial stability is another motivation mentioned in the literature. Managers try to smooth out earnings by delaying some of today's profits for tomorrow's losses, or pulling back some of tomorrow's profits to hide today's losses (DeAngelo et al (1996)). IPOs are also considered a major motivation behind earnings management. Teoh, Wong and Rao (1998) report that managers try to boost earnings around an IPO to attract more investors to trade it.

There is some satisfying evidence about the existence of earnings management which makes it hard to deny, albeit the main question in this thesis is to how is this linked with earnings forecast? As cited above, the literature pictures analysts' forecasts as part of public expectation and one of the incentives behind earnings management. However, assuming that managers are not mainly pressured by analysts' forecasts but by other factors, would earnings management have a reversal impact on the accuracy of these forecasts? There is no doubt that any unusual alteration in the company's accounts would make the life of analysts much harder to forecast the company's earnings. As a result, forecasters would become less accurate should managers attempt to use earnings management.

Therefore, this research will attempt to study how earnings management contributes to the forecast error conceded by the analysts. As earnings might get manipulated by some managers at some point in the year, the forecast error will look differently to what it's supposed to be if no earnings management is applied. While man studies have mentioned the role of accruals management in various aspects, earnings management has never been used as an explanatory variable of analyst forecast error. Besides, it will also study the major contributors to the forecast error such as the uncertainty of the company, previous performances and number of followers.

1.3.3. Market sentiment and analysts' forecasts:

Taking analysts' forecasts as a proxy of public expectation triggers behavioural scholars' attention to explore more about the behavioural aspects of this topic. A lot of conclusions drawn in the literature links analysts' irrationality or systematic lack of accuracy to behavioural or cognitive bias. This was clearly stated by DeBondt and Thaler (1990) who report that earnings forecasts are too extreme to be rational and that analysts overreact to previous information when making their forecast revisions. Similarly, Easterwood and Nutt (1999) brings up the same point by claiming that analysts' underreaction or overreaction to past year's earnings should be treated as an irrational behaviour.

At the same time, the literature attributes public expectation with market sentiment. Brown and Cliff (2004) defines market sentiment as the expectation of investors relative to a reference, where bullish investors expect returns to be higher than average and bearish investors expect returns to be lower than average. Similarly, Baker and Wurgler (2006) define sentiment as the tendency to speculate or the relative demand for speculation. Based on this, it is believed that analysts' forecasts contribute to the market sentiment but the literature does not consider these forecasts when estimating the market sentiment index.

Additionally, evidence regarding the impact of market sentiment on stock returns is quite contradicting. For example, while Baur, Quintero and Stevens (1996) find no association between future returns and sentiment levels, Baker and Wurgler (2006) show that sentiment shifts affect long term future stock returns. Brown and Cliff (2005) also find that sentiment level holds a predictive power for long-term stock returns and mainly from 1 to 3 years ahead. Furthermore, Chen (2010) finds that sentiment level plays a big role in a financial crisis, more precisely, the higher the market pessimism the higher the possibility of shifting from bull to bear market.

Furthermore, the value premium anomaly is one of the most popular stock market anomalies where value stocks appear to better than growth stocks in most of the financial markets. On the one side, the risk-based explanations led by Fama and French (1992b), Chen and Zhang (1998) and others, argue that this difference is a compensation to the financial risk associated to the high leveraged value firms. On the other side, behavioural finance scholars such as Lakonishok, Shleifer and Vishny (1994), argue that it is a result of naive investors making their decisions based on past performances. Therefore, investors tend to overvalue growth stocks and undervalue value stocks. A linkage between the market sentiment and the value premium was discussed by Schmelling (2009) who suggests that the impact of sentiment on stock returns is significant on both value and growth stocks. The author also finds that this impact is more significant in countries that have less regulatory institutions. Additionally, Baker and Wurgler (2006) find that young, unprofitable and growth stocks are negatively correlated by the sentiment level, that is, when sentiment level increases, stock returns of this type of companies decreases. Nevertheless, this result is found to be significant on the long term only.

Based on the above, it is believed that analysts' forecast error carries a sentimental component which, along with other factors, can have an impact on stock returns. To our knowledge, none of the the sentiment indices estimated in previous articles considers forecast optimism as a component of market sentiment. Taking forecast error as a proxy of market sentiment is not only based on simple definitions. This combination will help finding an answer of how a systematic optimistic forecast can still make an impact on investors and stock returns. Logically speaking, significant patterns in forecasts found by various articles such as systematic optimism (Bernhard and Campello (2007), Yu and Ke (2006) might affect stock returns to some extent but should fade away after some time as investors learn from their mistakes, which is not the case. Accordingly, the impact of forecast error on stock returns is believed to be reflected in an unavoidable market sentiment rather than having a direct effect.

This research will attempt to study the short term effect of market sentiment, as a function of forecast error and other proxies, on stock returns. The literature focuses on the long term effect of sentiment levels on stock returns (Baker and Wurgler (2006), Brown and Cliff (2004), among others), however, this research assumes that any long term impact is a reaction of an initial short term stimulation of the stock price and therefore stock prices are better observed on the short run when it comes to market sentiment.

The discussion made in this section provided a brief summary of the literature surrounding analysts' forecasts. However, there are many questions left unanswered and this thesis will try to cover many gaps in an attempt to offer a better understanding to the nature of analysts' forecasts and its implication on the stock market.

1.4. Research questions and key empirical findings:

A main motivation in this thesis is how the literature frames the analysts as naïve and biased on average. What if this was an effect of data mismanagement or external variables leading to the wrong conclusions? And if this is the case, what are these variables? Moreover, even if these forecasts are systematically irrational, how couldn't the market spot this gap yet keep on absorbing the information released by financial analysts? Contradicting results in the literature does not really help but makes these questions even bigger and in need of further investigation. These questions and more will be discussed in details throughout three empirical chapters concerning financial analysts' forecasts.

1- How accurate are financial analysts when forecasting the fiscal year-end earnings of FTSE all share companies?
2- How rational are financial analysts when making errors in forecasting?

The first two questions are posed to re-examine the accuracy and rationality of financial analysts. As stated earlier, analysts are proved to be overall optimistic in the literature in most of the financial markets. However, a lot of pitfalls in the data management is found in the literature and this research attempts to cover these gaps to provide an accurate investigation regarding the analysts' forecasts.

Using all available companies in FTSE all share from 1993 to 2013, findings in the first empirical chapter show that financial analysts are overall optimistic, however, not as extremely optimistic as the literature claims (DeBondt and Thaler (1990), Capstaff et al. (2001), among others). Moreover, the forecasts appear to become more accurate as the time approaches the earnings announcement date. Results also indicate that while analysts are being optimistic, there seems to be no significant sign of over- or under-reaction to available information. Despite the consistency in the findings with the literature regarding the optimism of forecasters, the results show some disparity in the magnitude of forecast error compared to previous studies. For instance, the yearly average forecast error shown in this study was much lower than Capstaff et al (1995) and Capstaff et al (2001)[3]. This difference difference is partially due to the fact that this study employs precise earnings announcement dates as opposed to the fixed three months' period following fiscal year end used by Capstaff et al (1995). Contrarily, Guedj and Bouchaud (2005) report a very low forecast error using a sample of only surviving and big companies. Surviving companies are the ones listed for on the stock exchange for a long period of time without being merged, acquired or delisted from the exchange. The sample employed in this study however, doesn't suffer from survivorship effect hence the forecast error appears to be slightly higher since all available companies were included.

Following DeBondt and Thaler (1990), the rationality of analysts' forecast is also investigated by testing the relationship between forecast changes and actual changes. Findings show that analysts revise their forecasts downwards but do not reach a perfect accuracy and the average forecast remains above the actual earnings. This result contradicts with previous studies suggesting that managers try to convince analysts to walk down their forecasts in order to generate a positive surprise by the end of the year (Richardson et al. (2004), Libby et al. (2007), among others). The theory of having realised earnings meeting or beating the analysts' forecasts cannot be confirmed in this chapter.

[3] Capstaff et al (1995) based their study on a UK sample, whereas Capstaff et al (2001) investigated European companies including the UK.

A second test of rationality tests whether analysts mis-react to previous year's earnings. A systematic over or under-reaction to previous year's earnings is considered a type of irrationality (Easterwood and Nutt (1999)). However, findings show that irrationality in analysts' forecasts is not statistically significant based on this specific test.

3- What is the relationship between earnings management and earnings' forecast error?
4- What is the impact of upwards earnings management on pessimistic forecasts?
5- What is the impact of the downward earnings management on optimistic forecasts?

Managers are well documented to to be managing their companies' earnings using accruals and real earnings management tools due to many incentives. Applying such manipulation is done internally leaving no possibility for information leakage. If this is true, such alteration will make the forecast error look differently to what it should be as realised earnings shift unexpectedly.

Accruals earnings management is estimated following the adjusted model of Dechow, Sloan and Sweeney (1995) and real earnings management is estimated following Roychowdhury (2006). Results show that earnings management positively affect the magnitude of forecast error, that is, when earnings are manipulated the forecast error appears to be larger.

After controlling for a set of other variables, the result seems to be dominated by the impact of accruals management and not by real earnings management. An extended analysis in this study was necessary to control for the endogeneity problem encountered from the possible reversal causality between analysts' forecasts and earnings management. The Generalised Methods of Moments GMM is employed to control for this possible problem by using lagged independent variables as instruments of the endogenous factor. Further analysis show that when earnings are managed downwards, forecasts appear to be more optimistic. This is due to the unexpected fall of earnings per share making forecasts look more optimistic than usual. The opposite is also true such that when earnings management is used to boost earnings, analysts' forecasts tend to be more pessimistic. Additionally, forecast error appears to be negatively associated with company's performance and positively correlated with company's uncertainty level. Companies with higher trading volume appears to have higher forecast error. One possible explanation is that higher trading volume attracts more followers and more speculation may weaken the forecast accuracy.

While previous studies have mentioned the role of earnings management in various aspects, abnormal accruals and real earnings management have never been used as an explanatory variable of forecast error. This study contributes to the literature by proving how earnings management play an important role in increasing the analysts' forecast error, the same analysts that the literature brands as irrational an extreme.

6- How does analysts' forecast error contribute to market sentiment?
7- What is the impact of analysts' forecast error and market sentiment on the value premium anomaly?

As stated in the previous section, it makes more sense taking the forecast optimism as a component of market sentiment, which might have an impact on stock returns. following Baker and Wurgler (2006), the market sentiment index is estimated using the first principal component of seven proxies: Forecast error, Market turnover, Number of IPOs, return on the first day of IPO, share of equity issuance, the dividend premium and the discount on closed-end mutual funds.

Findings show that forecast error is a major component of market sentiment and that they are significantly positively correlated. Additionally, results show that short term stock returns are positively significantly affected by market sentiment. This finding is inconsistent with Baker and Wurgler (2006), Brown and Cliff (2005), Baur, Quintero and Stevens (1996) who find that future stock returns are negatively affected by stock returns. Furthermore, figures from this study prove that stock returns are higher during high sentiment levels compared to low sentiment levels.

Companies are divided depending on their size and Book to Market in order to investigate the relationship between the estimated market sentiment and value premium anomaly. The analysis show that the value premium shrinks significantly when sentiment level increases. This is mainly driven by the sensitivity of growth firms towards sentiment shifts. As a result, small stocks, growth stocks and stocks with weak profitability are more prone to sentiment changes than value, large and stocks with robust profitability. This finding also contradicts with Brown and Cliff (2005) who report that sentiment only affects large and institutional companies.

1.5. Reasons for choosing the UK market:

The vast majority of articles in the literature investigating the analysts’ forecasts and earnings management are based on the US market. This thesis focuses on London Stock exchange in the UK as the main market under investigation for different reasons. There are many features that make the UK market special compared to the other markets around the world. London Stock Exchange LSE is considered the largest financial market in Europe in terms of cumulative market capitalisation of its listed firms, and the third largest in the world after New York Stock Exchange NYSE and NASDAQ in the US respectively. Moreover, it is the largest international capital market, having almost 3100 companies from more than 70 countries around the world with almost 700 of these are international (London Stock Exchange Group, 2017). LSE has specifically become very popular among Asian companies with 225 Asian equity issuers listed on the exchange, and since 2005, growing companies from China have raised over £2.6 billion on the market.

Many reasons have made LSE to become internationally characterised including its position at the heart of the global financial community. In addition, LSE runs several markets for listing, giving the opportunity for different sized companies to list, including FTSE100, FTSE 250, FTSE small cap and FTSE AIM (London Stock Exchange, 2017). Another reason could be the tight regulations imposed by the Securities and Exchange commission SEC in the US on public companies which might have led international companies seeking capital to choose London over New York. Taking as an example the entry requirements for an initial listing, LSE requires companies to have at least 75% of the entity’s business supported by a revenue track record for the 3 years’ period, and a minimum market cap of GBP700,000 (PWC, 2012). For the same companies NYSE requires to meet at least one of the following points (PWC, 2012):

1- Income before tax contintuing operations and after minority interest, amortisation and equity in earnings or losses of investees must total at least to $10 million in aggregate for last 3 fiscal years, together with a minimum of $2 millin in the most recent fiscal year and $2m in the next most recent fiscal year.

2- Or, Issuer must have at least \$500 million in global market cap, \$100 million in revenues in the most recent 12month period, and \$25 million in aggregate cash flows for the last 3 fiscal years with positive amounts in all 3 years.
3- Or issuer must have at least \$150 million in global market cap, and \$75million in total assets together with at least \$50million in stockholders' equity.

These requirements highlight the differences between the UK and the US markets. For these factors and more, outputs from studies based on London Stock Exchange would most likely differ from other research studies about NYSE.

As regarding the topics covered in this research, forecasting companies' performances can take a different approach due to the different disclosure policies in the United Kingdom. Previous studies show a significant association between corporate disclosure and analyst's forecasting accuracy (Lang and Lundholm (1996), Ang and Ciconne (2001), among others), as higher amount of accounting disclosure leads to less forecasting error. In this manner, La Porta et al (2006) reports the US companies are more extensive and formal in their disclosure material compared to UK firms. Ang and Ciconne (2001) find evidence that analysts that follow companies with more disclosure material tend to be less volatile in their forecasts.

Moreover, while companies listed on the main market in the UK must comply with the International Financial Reporting Standard IFRS, the US has been trying gradually to converge to the IFRS ever since the Enron scandal in 2002, but most of its listed companies still adopt the US GAAP. According to Fosbre, Kraft and Fosbrej (2009, page 66), "Many areas of accounting standards remain to be comprised and converged. Other differences also exit. Measurement of interpretations includes IFRS standards which are for the most part are more broad and principle based as compared to US GAAP. US standards contain underlying principles as well as strong regulatory and legal requirements". These differences can partially lead to differences in the way financial analysts perceive accounting information. Moreover, earnings management is also believed to be perceived differently between the UK and the US. Frederikslust et al (2007) explain that in the UK there exists less fiduciary obligations on directors but more minority investor protection than in the US. Less fiduciary obligations might allow managers to be more flexible in managing discretionary accounts in order to manage their earnings in a favourable way. From a regulatory and environmental perspectives, part of the the existing differences and between the UK and the US markets will eventually lead to different results in the research regarding the analysts' forecast performance.

1.6. Research philosophy

According to Ryan, Scapens and Theobald (2002), there are three major issues that could be argued upon when trying to define knowledge in research: The nature of belief, the basis of truth and the problem of justification or research approach. The debate regarding the nature of belief is unavoidable in any research material and this thesis is not an exception.

The philosophy surrounding this research looks at the reality from a positivist standpoint. Gill and Johnson (2010) defines a positivist researcher as the one who prefers to collect data in order to observe some regularities and causalities that exist thorough relationships, and in the end creates a law-like generalisations such as theories. Before them, Friedman (1953) explains that the main objective of positive economics is to develop a hypothesis that will lead to a valid and meaningful representation of a phenomena not yet observed. The research approach applied in each chapter fits very well into this description since it follows the process of deduction (testing hypothesis to prove a systematic scenario), and in the end it comes back to link the findings and interpretations to the theory through an induction stage.

The main assumption in the positivism philosophy according to Crotty (1998) is that "the researcher is value neutral, although absolutist claims that the outcome is totally objective and unquestionably certain are made rarely". As such, the reality is believed to be existing and the tool to observe this reality is by acquiring credible and reliable data that reflects it the best. This research examines different issues and patterns in the stock market such as the rationality of analysts' forecasts, earnings management and the value premium that are believed to exist, then tries to test the hypothesis related to each issue by reaching out to quantitative secondary data. The data collected is based on stock market and consists of automated trading data such as stock prices, trading volumes and many more. It also consists of company's reports generated by the performance of real activities throughout the quarters and fiscal years. Further discussions regarding how suitable the data is for the questions posed could be seen in each empirical chapter.

Saunders, Lewis and Stonehill (2012) explain that the positivist approach to research is value-free. They add that a researcher adopting this philosophy "would claim to be external to the process of data collection in the sense that there is little that can be done to alter the substance of the data collected". As a matter of fact, the same applies to the nature of analysis conducted in this research. The dominant method in this research, which is also classified under the problem of justification, is based upon empiricism by providing empirical chapters to test certain hypothesis. However, it also accepts the distinction between observation and theoretical terms. Additionally, it also confirms that assumptions are essential before setting a hypothesis of an empirical model, which in turn will lead to proving an implication.

The arguments given in this section reflects to a great extent the research philosophy in the area of finance and economics. As it tries to provide the best possible explanation to knowledge, this research makes sure that the research questions are unchanged by the decision of research philosophy.

Chapter 2:

Accuracy and Rationality of Analysts' Earnings forecasts in the UK

Chapter 2: Accuracy and Rationality of Analysts' Earnings Forecasts in the UK

Abstract

Financial analysts are believed to play a major role in driving financial markets. Any error or bias in financial analysts' forecasts is likely to mislead investors who rely on these forecasts to make big investment decisions. Previous papers suggested that for many reasons, financial analysts might make systematic errors rather than just being a result of an unsystematic human being mistake. The rationality and bias of financial analysts are investigated in this chapter for UK public companies. In order to study the accuracy of analysts on the index overall, FTSE all Share companies are collected individually as available for each year from 1993 to 2013. Two measures of forecast accuracy were used. First, earnings per share forecast error to show how far forecasts are from actual earnings per share. Second, forecast bias that represents analyst's optimism or pessimism regarding company's performance. In addition, the horizon effect is examined by observing forecast errors from 11 to 1 month prior to earnings official announcement date. After setting few criteria to control for outliers, results show that analyst forecasts are overall optimistic. However, they seem to diverge to a more rational position the closer they get to the announcement date. Despite no evidence of relationship is found between forecast error and prior year change in earnings per share, analysts are proved to be systematically revising their forecasts downwards from the beginning of the year until the earnings announcement date. These results prove that forecasts are inefficient and raise more questions about bias of analyst forecasts and its implication on stock markets.

Chapter 2: Accuracy and Rationality of Analysts' Earnings Forecasts in the UK

2.1. Introduction

Since earnings forecasts constitute an essential part in the process of stock valuation, financial analysts have become an important source of information that directly influences the stock floating prices. Almost all the models such as the discounted cash flow valuation model and the analytically equivalent residual-income valuation model rely directly or indirectly on forecasting. Accordingly, analyst's forecasts are taken into consideration in any investment decision. However, it is almost impossible for an analyst to forecast a company's future earnings with perfect accuracy. The reasons behind this shortcoming could be explained by lack of information, companies' performances being hard to predict, or even errors made on purpose by analysts for different motivations. Consequently, such topic has attracted many researchers to study the determinants of analysts' accuracy in order to find a reasonable explanation for the error in earnings' forecasts and its implication on stock markets (Becker, Steliaros and Thomson (2004); Capstaff, Paudyal and Rees (2001)…). The importance of this topic lies behind the fundamental intermediate role financial analysts play in the market. When analysts make big errors in forecasting a company's earnings, they may mislead investors who follow that specific company to make the wrong investment decisions based on the analysts' false recommendation. Add to this, if consensus analysts make big forecast errors, this will lead to larger amount of related investment decisions that might result in a negative overreaction when the realised earnings are released otherwise (due to the overestimation of earnings).

The literature shows that analysts forecasts are overall optimistic in regards to companies' future earnings (Capstaff et al. (2001), Gu and Wu (2003), Easterwood and Nutt (1999), Ciconne (2005), Larocque (2013)). Capstaff et. Al. (1995) argue that financial analysts might have the incentives to issue optimistic forecasts in order to increase the trading volumes generated after their forecasts. Abarbanel and Bernard (1992) find that stock prices drift after earnings announcement are partially driven by inefficient forecasts made throughout the year. Mest and Plammer (2003) explain that optimism in analysts' forecasts facilitate the access to management's private information especially for hardly predictable firms.

Other studies relate the forecast accuracy to other factors such as the country effect (Ang and Ciccone, 2001). The level of development, the growth rate, the economic risk, the level of competition between firms, the legal and institutional environments and the financial and accounting systems are all found to be sources of influence related to each country separately. The industry effect also featured in many studies related to the analysts' forecast accuracy. Capstaff et al. (2001), for example, find that public utilities and health-care sectors have more accurate forecasts than transportation and consumer-durables sectors. The stability of firms in each industry sector was given as a possible explanation of this variable.

Despite providing statistical evidence of the forecast error made by analysts, a lot of articles are prone to data limitation that might have led to many results being spurious. To examine the accuracy and bias in analysts' earnings forecasts, most researchers use consensus forecasts (Average of yearly, quarterly or monthly forecasts) and compare it to the realised earnings at the end of the year to see how accurate analysts are. However, past UK studies suffer from sample and technical limitations due to several reasons. For example, Beckers et al. (2004), Ackert and Athanassakos (2003) and Das et al. (1998) use firms with December fiscal-end years only. This is due to the complexity of merging data for companies with different fiscal year end. Nevertheless, this study shows that if only December fiscal year-end firms were taken into consideration, we would be ignoring 58% of the companies that end their fiscal year in different months. Another data weakness was shown in Easterwood and Nutt (1999) and Larockque (2013) who ignore the first 4 months of the year to insure that previous financial report has been announced. Findings in this chapter show that different companies release their financial reports in different months. More precisely, there exists 11% of FTSE all share companies that take more than 4 months to release their reports. Additionally, 34.6% of companies take only 2 months to release their results and in this case, the literature would be ignoring 2 months of consensus forecasts that should've been included in the yearly average. Furthermore, Guedj and Bouchaud (2005) restrict their sample to a fixed number of US, UK and European firms all over the period from 1987 to 2004. Again, the analysis in this study show that only big and strong companies survive as public throughout this long period. This means that applying such criteria would eliminate small growth companies that are harder to predict.

The values generated from such restricted samples, however, can lead to bold conclusions that are then referenced across the literature from behavioural finance (DeBondt and Thaler (1990), and asset pricing (Larocque (2013), Hribar and McInnis (2012)). This chapter focuses on how such a restricted sample can lead to different results, and why having a complete and comprehensive sample can rebuff previous conclusions made about analysts' forecasts.

Therefore, this research uses FTSE all Share companies in London Stock Exchange as the main sample under investigation. All available companies in each year from 1993 to 2013 were collected individually and included in the analysis. In addition to employing a better representative sample of the UK firms, the horizon effect in this study is examined by observing monthly forecasts from the beginning until earnings announcement date rather than the fiscal year-end. Findings show that financial analysts are optimistic, however, not extremely optimistic as the literature claims (DeBondt and Thaler (1990), Capstaff et al. (1995)). Nevertheless, forecasts are not as precise as Guedj and Bouchaud (2005) shows. This is reasonable due to the inclusion of small and harder to predict companies.

Follwing DeBondt and Thaler (1990), the rationality of analysts' forecasts is also investigated by testing the relationship between forecast changes and actual earnings changes. Such test can illustrate if there is a trend in the forecasts throughout the months until the end of the year. Results show that analysts revise their forecasts downwards from when they start forecasting in month 1 until just before the earnings announcement date. However, this is valid for optimistic forecasts only. Albeit, figures for this test are less aggressive than findings in Capstaff et al. (1995) who find sharper downward revision trend of -14.8% compared to -9.7% in this study. An interesting factor in this result is that the forecast remains above the actual earnings released in the last month of forecast, even with a steady downward revision throughout the previous months. This result contradicts with previous studies suggesting that managers try to convince analysts to walk down their forecasts in order to generate a positive surprise by the end of the year. The theory of realised earnings meeting or beating the analysts' forecasts cannot be confirmed in this chapter.

Additionally, a second test of rationality is applied following Easterwood and Nutt (1999). Under this test, irrationality is when forecasters show systematic underreaction or overreaction to past year's earnings, which is considered a mistreatment of information and therefore defined as irrational behaviour that could lead to serious trouble in financial markets. Contrary to Easterwood and Nutt (1999) and Abarbanell and Lehavy (1992), results in this chapter show that irrationality in analysts' forecasts is not statistically significant based on this specific test.

This chapter contributes to the literature of financial analysts' forecasts in many ways. The analysts are often seen in the literature as overly and extremely optimistic (DeBondt and Thaler (1990), (Capstaff et al. (1995) and Larocque (2013), among others), and this has led many studies to base this suggestion on financial behaviour issues, or link this factor to sell-side analysts who aim at increasing the trading volumes rather than being accurate (Capstaff et al. (1995)). Results in this chapter using the main analysis in addition to robustness checks show that this suggestion doesn't hold. The high values of forecast errors diminish when taking into account all the windows from the start of the year until just before the earnings announcement date. The main reason for this decrease was mainly assigned to studies not taking into account the last few months before the announcement date (by taking the fiscal year end as a closing date rather than the reporting date for example). At the same time, analysts are not perfectly accurate regarding the UK companies' performance. The estimations in this chapter show that there is a degree of error in their forecasts contrarily to some previous studies such as Beker et al (2004). This main difference is believed to be due to the survivorship effect, taking December fiscal year end firms only, and other sampling restrictions.

Furthermore, as other limitations are taken into consideration, a fair and representative sample indicates that analysts' forecasts are not subject to trendy revisions, neither irrationality in using past earnings information, leading us to conclude that they are not purposefully biased but simply concede errors within acceptable norms.

The remainder of this report will come as follow. A background of earnings forecasts studies and a review of the literature come in the second section. A critical review of previous studies will help to set up the hypothesis of this research at the end of the second section. The third section includes Data and Methodology in which sample selected and forecast error measures will be explained. Results, tables and figures will be introduced in this section as well.

2.2. A Review of the Literature:

Forecasting future earnings was never considered an easy job for an analyst since it involves a mixture of micro and macro variables that if changed by small fractions, might diverge the forecast by a significant proportion and thus harm any investment based on it. In 1975 John Gillis published *"the legal aspects of corporate forecasts"* in a move to avoid an exposure to liability and an increase in litigation in the US stock market due to the inaccuracy of analysts' forecasts and legal uncertainties caused by the US Securities Act of 1933. Gillis (1973) therefore explained some appropriate points that should be considered in any forecast. The assumptions are divided into three categories:

i. General and economic factors:
   a. General economic conditions
   b. National and International conditions
   c. Wage and prices
   d. Monetary policy
   e. Federal budget
   f. Financing costs
   g. Restrictions on corporate dividends
ii. Industry factors (in which a company operates) :
   a. Growth rate
   b. Availability of raw materials
   c. Continuity of markets
   d. Acceptance of products
   e. Labour status.
iii. Firm specific and employees' factors:
   a. strikes
   b. wage settlements
   c. start-up or break-in problems with new products or processes
   d. overestimation of new product demand
   e. cost overruns
   f. construction delays

Ignoring some of these factors might lead to a large forecast error (Barefield and Comiskey (1975)). Since less attention was given before 1975 to earnings forecasts made by security analysts, Barefield and Comiskey (1975) study the performance of analysts who forecast year-end earnings of 100 company of New York Stock Exchange, and compare it to managements' expectations of earnings per share. They find overestimations in 64% of the cases, in which the average analysts' forecasts exceed the realised earnings. While analysts showed a robust performance by predicting most of the earnings turning points, it remained hard to explain the large prediction error since little is known about the analysts' forecasting procedures.

While many researchers use a wide set of time-series data in order to make robust assessment on the results, Fried and Givoly (1982) claim that earnings' forecasts based on time series models alone are inappropriate since they assume that earnings are stationary to form their predictions, thus analysts' forecasts are considered as better proxies of future performance[4]. Consequently, Fried and Givoly (1982) tend to use FAF "financial analyst forecasts" as a surrogate for market expectations. On a sample of 10 years, only NYSE listed companies with fiscal year ending on December 31st were included. The companies should also have at least 4 forecasts per fiscal year and an availability of monthly return for the current year, the following year and the preceding four years. In the end, they find that financial analyst estimates are better predictors than the ordinary time-series forecasting models and this might be due to two reasons. First, the flexibility to use wider set of information including non-accounting information about the firm, industry and general economy. Second, the flexibility in the timing of forecast since they can include news about earnings released during the forecast period.

2.2.1. Earnings Forecast Errors: Different Measures and Different Perspectives:

Most of the literature uses the traditional approach which denotes that the analyst forecast error is equal to the difference between "actual earnings" and "forecasted earnings" at a given time, divided by "actual earnings" or "Forecasted earnings". However, other measures were also used in order to observe analyst forecast accuracy. Brandan and

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[4] Chapter 3 uses lagged values of earnings management estimations in a Generalised Methods of Moments model. Despite not having a unit root existing, a big advantage of the System GMM is that it overcomes non-stationarity when having a panel data of N (number of subject observations) being much larger than T (number of periods), which is the case in chapter 3. Moreover, "in the existence of panel data, and observations among cross-sectional units are independent, then one can invoke the central limit theorem across cross-sectional units to show that the limiting distributions of many estimators remain asymptotically normal" (Cheng, 2006, p.7).

Jarrette (1975) summarise these different measures of forecast error. According to the authors, the concept of forecast should be approached by estimating the loss function of its inaccuracy. They therefore divide the loss function into two: Linear loss and Quadratic loss.

The Linear loss function is the traditional approach which is equal to the difference between Actual earnings and forecasted earnings divided by the actual earnings. “Another variation of this measure, where the sign of the deviation is of no consequence, is the mean absolute error” (Brandan and Jarrette (1975)).

$$1 - FE_T = \frac{F_T - E_T}{|E_t|}$$

$$2 - |FE_T| = \left|\frac{F_T - E_T}{E_t}\right|$$

Where FE is forecast error at time t, Ft is the EPS forecast at time t, Et is the actual EPS at time t.

Other people tend to use different denominators such as “Stock Price” (Ali, Klein and Rosenfeld (1992)), Forecasted earnings per share (Dreman and Berry (1995)), standard deviation of actual eps (Dreman and Berry (1995)).

The concept of non-linear forecast error (Quadratic loss function) came from the implication of non-accurate forecasts on the market. Brandan and Jarette (1975) state: “(…) if inaccurate forecasts lead to decisions with dramatic negative consequences (loss), then the seriousness of the forecast inaccuracy is equivalently large. In statistics this loss criterion has a prominent place, e.g., as a minimum variance estimation where the size of the error is universally related to the predictive ability of the estimator”. Accordingly, the forecast error will be squared to reflect the implication of such a mistake in the real life transactions.

Mathematically this could be translated by the following:

$$MS = E(P - A)^2 = (P - A)^2 + S_P^2 + S_A^2 - 2R_{PA}S_PS_A$$

Where MS is the mean square error as a measure of forecast accuracy. MS is a function of the mean of the predicted series, its standard deviation and the correlation between predicted and actual series. P is the mean of predicted values, A is the mean of actual values. S is the standard deviation and r is the correlation. This quadratic loss function is also used by Lim (2001) who developed a model combining private information noise with public information available to a financial analyst. In the end, he argued that if an analyst is optimistic doesn't mean irrational, however, it means predictably biased. More specifically, if an analyst's priority is accessing private information through companies' management, and then they are predicted to be associated with more optimistic forecasts especially if the sought after companies' information is vague.

In order to address the role of time series correlation in the forecast accuracy of analysts, Ali, Klein and Rosenfeld (1992) regress the forecast errors made by analysts at time t, to their previous forecast errors in addition to the previous return on stocks. They use the traditional approach to calculate the forecast errors (Analysts forecasts of earnings minus realised earnings divided by the stock prices when the forecast was made). They find that individual forecasts of annual earnings are correlated in adjacent years. According to them, "one interpretation compatible with our results is that analysts systematically underestimate the permanence of past forecast errors when forecasting future earnings. That is, they do not appear to properly incorporate information about the time-series properties of earnings into their forecasts" Ali, Klein and Rosenfeld (1992, page 188).

A further study on the US market is done by Dreman and Berry (1995) who compare 66100 consensus analysts' forecasts, and find that the average earnings forecast is significantly different than the actual earnings. In order to analyse 17 years of quarter earnings estimates, they calculate a "standardised surprise measure" (known as forecast error), by dividing the difference of forecasted earnings and actual earnings, by the standard deviation of actual earnings. By doing this, they aim to test the volatility-adjusted error on the whole sample and for each industry-yearly sample. Besides, they use four measures for the forecast surprise known as error:

SURPE=Consensus EPS surprise as a percent of absolute value of actual EPS= (actual quarterly earnings-Predicted quarterly earnings)/|Actual quarterly earnings|

SURPF= Consensus EPS surprise as a percent of absolute value of predicted EPS= (actual quarterly earnings-Predicted quarterly earnings)/|Predicted quarterly earnings|

SURP8= Consensus EPS surprise as a percent of past eight-quarter volatility of actual EPS= (actual quarterly earnings-Predicted quarterly earnings)/|standard deviation of past actual eight-quarter EPS|

SURP7= Consensus EPS surprise as a percent of past seven-quarter volatility of actual EPS= (actual quarterly earnings-Predicted quarterly earnings)/|standard deviation of the past actual seven-quarter change in EPS|

Moreover, Dreman and Berry (1995) also create a second sample by deleting all the firms who have a reported or forecasted EPS between -10 and +10 cents, in other way, deleting all firms who have small EPS. They argue that using this technique could prevent potential outliers to dominate the result, and control for a large part of this negative bias problem for the surprise metrics. Their approach was logically fair since using a small or negative actual or forecasted EPS as a denominator would deteriorate the analysis. Nonetheless, their results show that the average forecast error is more than 20% of the realised earnings per share, which is "(…) too high for investors to rely on consensus forecasts as a major determinant of stock valuation" Dreman and Berry (1995, page 39). They also find that the error rates are increasing over time, and are not affected by the industry groupings. Using a different database (IEBS database), Brown (1997) find similar results of large forecast errors from 1983 to 1996 of quarterly data. However, the author adds that analyst forecasting errors have significantly decreased over time except for "S&P 500", contrarly to Dreman and Berry (1995).

2.2.2. Analyst Forecast Bias and possible explanations:

An extensive body of the literature tried to examine the information content of earnings by studying the relationship between analysts' forecasted earnings and future stock prices. Most of these studies find evidence of the inefficiency of the market after they discovered abnormal stock returns following the release of analysts' results (Foster (1977), Watts (1978), Givoly and lakonishok (1979)). Other studies also focus on how accurate analysts could be in forecasting future earnings. In a sample of 185 corporations between 1962 and 1963, Cragg and Malkiel (1968) show that analysts' predictions are more accurate than using past data variables such as past earning growth rates and past P/E ratios. The authors, however, argue that they couldn't directly prove whether these good results were due to analysts' abilities, since only few analysts were able to participate in the study.

Since forecasting future earnings is affected by private and public news, this will give signals to the analyst depending on the time of news given. De Bondt and Thaler (1990) attempt to find an explanation why analysts' forecasts are mostly too optimistic and too extreme in a study of forecasts between 1976 and 1984 of NYSE companies. Two market variables are included in the model in order to explain the large forecast error: Market value to book value of equity (MV/BV), and earnings growth. However, none of the variables explained much of the error. They reach a simple conclusion that behavioural bias is behind this error since analysts are decidedly human, and their results could be biased in some way or another.

Chopra (1998) reports that analysts overestimate earnings at the beginning of the fiscal year by an average of 9.4% between 1985 and 1992, but they seem to improve their forecast accuracy after revising their forecasts every month as they get closer to the end of fiscal year. Moreover, Chopra (1998) also discusses the relationship between economic growth and EPS growth. The author uses the industrial production growth as a measurement of the economic growth and concludes that when this growth accelerates, earnings grow slowly and the gap between optimistic growth forecast and actual earnings growth narrows, leading to a more accurate forecast.

Contrary to other studies, Tamura (2002) focuses on individual analyst's characteristics when observing forecast errors rather than taking the consensus of overall analysts. According to the author, one should calculate first the forecast error for each analyst who follows some firms then take the average of all individual forecast errors calculated to regress it and find the reason behind it. The reason behind this idea is that analysts' forecasts are strongly affected by their personalities (optimistic or pessimistic) and the way they might underreact or overreact to some news. Easterwood and Nutt (1999) examine the forecast accuracy by differentiating three hypotheses regarding the reaction of analysts: Analysts systematically underreact to earnings news; analysts systematically overreact to earnings news; and analysts are generally optimistic to new information. According to the researchers, discriminating between them is important "(…) because it might indicate whether analysts irrationally err in processing earnings-relevant information or whether their forecast errors are more consistent with their economic incentives". While the first and the second hypotheses are independent of the type of information, their test proves that analysts underreact to negative information and overreact to positive information, with an overall optimistic interpretation of information. Easterwood and Nutt (1999) also find that analysts tend to underreact to abnormally negative news and overreact to abnormally positive ones, after they revise their prior year error.

Gu and Wu (2003) stress that since analysts aim to produce the most accurate results by minimising the mean absolute error, then the median should be used instead of mean earnings. Moreover, the writers find evidence that “part of the observed analyst forecast bias could be a result of analysts’ efforts to improve forecast accuracy when the earnings distribution is skewed”. After regressing skewness over the forecast bias, the results showed a significant relationship between earnings skewness and earnings forecast bias at 1% confidence level.

Other researches have employed more sophisticated approaches by relating the forecast accuracy to the country effects (Ang and Ciccone (2001)) or the industry effect (Capstaff et. Al(2001)). The level of development, the growth rate, the economic risk, the level of competition between firms, the legal and institutional environments and the financial and accounting systems are all sources of influence related to each country aside. In a sample of European countries between 1987 and 1994, Capstaff et al. (2001) find that public utilities and health-care sectors have more accurate forecasts than transportation and consumer-durables sectors. The stability of firms in each industry sector is given as a possible explanation of this variable.

Ciconne (2005) proposes a new idea by separating firms with profits and losses in the analysis of forecast error. The final sample includes 120022 firm-quarter , 94194 quarters with profit and 25828 quarters with losses. While analyst dispersion and forecast error are the dependant variables used in the models; Size, Book-to-Market ratio, a Loss dummy variable, and Year dummy variables were used as independent variables. The result from Ciconne (2005) shows that loss firms’ earnings are more difficult to predict with a forecast error bigger than the ones with profits. In addition, forecast errors are decreasing over time and analysts were not as optimistic as the literature proved. Due to the bad reputation they may receive when they mislead investors which will affect their future, the incentives to receive private information can no more compensate the risk of failure for the analysts (Ciconne (2005)). Similarly, Coen et. Al. (2009) specify three factors affecting the forecast errors: Country effects, Industry effects and Firm specific effects which include firms’ Analyst following, change in earnings, and profits/losses. Their analysis show that forecast error of 18% is much larger for firms’ that reported losses than those that reported profits (1.8%). These findings are consistent with Ciconne (2005). Moreover, they add that analysts forecast performance is much weaker for firms’ that saw a decrease in earnings than those that saw an increase in earnings. Finally, Firms' followed by more analysts had more accurate forecasts.

Latterly, Henderson and Marks (2013) use the profit margin (including earnings and revenues) as an explanatory variable in the forecast error analysis. Contrary to previous studies, they focus on the change in profit margins that an analyst is expecting to see relatively to previous years' value. Henderson and Marks (2013) explains that: "The underlying idea is that observation of the net profit margin implied by analyst forecasts provides a reference point from which earnings and revenue forecasts can be judged to be extreme and thus inaccurate". Their findings show a pessimistic bias in earnings and revenues forecasts.

The time at which analysts release their forecasts was investigated by Baron, Biard and Liang (2013). They find that a pessimistic forecast is issued later than the other forecasts on average, which may explain why the last quarter of a fiscal year is less optimistic in terms of earnings forecast.

2.2.3. Relationship between managers and analyst forecasts:

On the one hand, one of the most noticeable reasons behind the change in forecast errors is thought to be earnings management. Managers often decide to manipulate the reported earnings via intangible accounts such as accruals, in order to get advantage of some benefits as an increase in stock price, getting a better reputation or bonuses. Degeorge, Patel and Zeckhauser (1999) for example denote the following:" The rewards to a firm's senior executives—both employment decisions and compensation benefits—depend both implicitly and explicitly on the earnings achieved on their watch (Healy 1985). But such executives have considerable discretion in determining the figure printed in the earnings report for any particular period. Within generally accepted accounting principles (GAAP), executives have considerable flexibility in the choice of inventory methods, allowance for bad debt, expensing of research and development, recognition of sales not yet shipped, estimation of pension liabilities, capitalization of leases and marketing expenses, delay in maintenance expenditures, and so on. Moreover, they can defer expenses or boost revenues, say, by cutting prices. Thus, executives have both the incentive and ability to manage earnings. It is hardly surprising that the popular press frequently describes companies as engaged in earnings management—sometimes referred to as manipulation".

On the other hand, Mest and Plummer (2003) propose that companies' managers play an important role in the biases of analysts forecast since optimistic forecasts can improve the chance for an analyst to access the management. Therefore, if management give less attention to the forecasted measures, analysts will turn to be more rational and accurate. Accordingly, they test this prediction by examining sales and earnings forecast and find that analysts' forecasts are too high. This hypothesis is consistent with the findings of Das, Levine and Sivaramaknishnan (1998) who point out that since optimism in analysts' forecasts facilitate the access to management's private information, analyst will demand more non-public information for hardly predictable firms by issuing optimistic forecasts. Following Kang et al. (1994), Das et al. (1998) use the horizon effect, which consist of having four different forecast times during a fiscal year, to forecast the end of this fiscal year. For example, horizon 1 will be the farthest forecast from the year-end earnings and horizon 4 the closest.

Therefore, the authors calculated BIAS term for each horizon separately as follow:

$$BIAS_n = \frac{1}{N_n}\sum_{t-89}^{93}\frac{A_t - AF_{nt}}{P_t}$$

Where N refers to the number of forecasts for a specific horizon n between 1989 and 1993; A is the reported earnings per share during the year t (which is comes 1989 and 1993) ; AF is the forecasted earnings per share at the horizon n for the year t and P is the share price at the fiscal year-end t. After calculating the BIAS term, they regress it against the Earnings predictability (UNPRED) which represents how hard is to predict firms' future earnings from historical information, and firm size. Results show a negative BIAS for all horizons during the studied period, which indicates optimism since Analyst forecasts are larger than the realised earnings. The UNPRED was significantly negative for all 4 horizons, insisting that when analysts cannot predict future earnings using historical data they tend to be optimistic about their forecasts and in need of private information.

Eams and Glover (2003) re-examine the work of Das et al (1998) by studying the association between earnings forecast errors and earnings predictability. After controlling for earnings level, they conclud that there was no evidence regarding the association between earnings forecast errors and earnings predictability. Besides, they couldn't prove that analysts intentionally issue optimistic earnings.

Lately, the relationship between managers-analysts and its impact on analysts' forecasts have been re-examined by Ke and Yu's (2006), Libby et. Al (2007) and Bernhardt and Campello (2007). Ke and Yu's (2006), Libby et. Al (2007) state that not only analysts have an advantage in having good relationship with managers, managers may indirectly force analysts to release good reports regarding their company, as a trade off with accessing private information. Bernhardt and Campello (2007) report that firms might, on purpose, generate earnings that exceed analyst forecasts, in order to make a positive surprise and stimulate the stock prices, and this could be done via various accounting methods. According to the same authors, it is possible that a company put pressure on analysts to issue lower earnings forecasts thus the earnings surprise will also be positive. The authors focuse on Quarterly data from Institutional Brokers Estimate System (IBES), and gather data prior to the US Regulation Fair Disclosure from 1989 to 1999. They find that late forecasting news have more impact on investment decisions than early ones. Beside, firms for which the forecasts falls just before the announcement date earn far higher returns around the announcement period than those which have high earnings expectations with an impressive difference of 69%.

Larocque (2013) investigates whether analyst forecast errors and cost of equity capital estimates are related using Ali et al. (1992) model. After estimating the predictable analyst errors, Larocque (2013) relates the adjusted forecast error (unpredictable errors) to form a better proxy to the market expectation of equity return, which in turn might affect the realised return in the future. However, even after this adjustment, no evidence of correlation was found between cost of equity estimates and realised returns.

2.2.4. Simultaneous regression Models:

One of the main assumptions of a single-regression model is that analysts' behaviours are treated exogenously, in order to separate it from the behaviour of other market participants. However, the relationship between analysts' accuracy, number of analysts and trading volume appears to be endogenous for many reasons. On the one hand, the more analysts following a certain company, the bigger the amount of information uncovered about this firm. Since more efforts are made on the same company, this will result in a better accuracy. On the other hand, trading volume will attract more analysts since improving investments will improve liquidity and commissions depending on the reputation, thus analysts' role will be more valuable in this manner. If this was true, doubts will be raised regarding the use of a simple regression model.

Alford and Berger (1999) criticize the single-regression models by using a simultaneous equations analysis including forecast accuracy, analyst following and trading volume. They responded that the old single-regression misrepresent the relationship. The use of analyst following in their research reflects the amount of information privately gathered about a firm which is, according to them, "complements rather than substitute the factors that increase certainty about firms' prospects" (Forecast accuracy). Therefore, the use of simultaneous equations was essential in their research. Their results show greater analyst accuracy associated with higher analyst following. The impact of accuracy on following is also consistent as analysts preferring to follow firms about which there is less uncertainty. Moreover, stocks that generate higher brokerage commission has higher analyst following. In addition, Alford and Berger (1999) extend the existing literature by adding several new explanatory variables to capture the economic changes in a company, these variables including "lagged magnitude of special items" and "lagged value of signal based on the fundamental variables" which is used by Lev and Thiagarajan (1993)".

Another simultaneous regressions model was developed by Ackert and Athanassakos (2003) who study how analysts respond to institutional demand of stocks, on a sample of 72,141 monthly observations for 455 firms collected from Institutional Brokers Estimate System (I/B/E/S). The three simultaneous equations were set to model the analyst optimism, analyst following and Institutional ownership. The idea of including institutional demand of stocks, which is the change in institutional holdings, was explained as follow: "Despite their bias or optimism, professional financial analysts act as information intermediaries. They provide research reports that are a useful source of information, as evidenced by investor demand. At the same time, securities firms use analysts' reports as drawing cards. Multi-service firms may attract institutional business through the research reports produced by their analysts. Institutions then use this information to make investment decisions. Moreover, institutional investors demand analysts' reports in order to provide evidence of adequate care and comply with fiduciary responsibilities" Ackert and Athanassakos (2003). After conducting the analysis, they report that higher analyst optimism leads to higher institutional demand. Moreover, forecasts are less accurate for stock prices that had recently increased.

2.2.5. Analyst forecast bias in the United Kingdom:

Until the second half of the 80's, little attention had been given about analysts' nature of work and its implication on the stock market in the UK. Arnold and Moizer (1984) conduct a survey to discuss the appraisal methods used by UK investment analysts. Other than the financial annual reports, relationships with insiders such as company management were viewed as the most important source of information used by analysts. Furthermore, the analysis of past financial data was seen to be far less useful to analysts in the attempt to interpret future price movements (Arnold and Moizer (1984)). Pique et. al. (1993) analyse how the implementation of new technology and the "Big Bang" deregulation in the UK market have changed the equity valuation approaches used by analysts. They find that while fundamental analysis using P/E multiple remains the dominant method in the stock valuation, the discounted cash flow and beta analysis enjoyed little support.

Bhaskar and Morris (1984), Patz (1989) and Capstaff, Paudyal and Rees (1995) were among the first to address the UK companies in regards to rationality of earnings forecasts. Samples used in Bhaskar and Morris (1984) and Patz (1989) are considered relatively small compared to nowadays studies. Consistent with the literature in the US, both papers reported evidence of analyst' forecast superiority over naïve forecast methods such as time series. Capstaff, Paudyal and Rees (1995) also make a contribution by focusing on individual forecast rather than taking consensus forecasts. According to the authors, "(…) the behaviour of the consensus may not be informative regarding the behaviour of individual forecasts as, for example, unsystematic errors made by individual analysts may cancel out. In addition, errors in the data such as outliers, or even bizarre forecasts might diffuse in the averaging process. The possible reasons behind analysts' inaccuracy are that analysts in some cases may not be motivated to maximise the accuracy, particularly when they have incentives to increase the volume of trade generated after their forecasts". This explains the overreaction of market prices after optimistic forecasts discussed in the literature. Capstaff et. Al. (1995) then test analysts' rationality by regressing the forecast change to the change of actual reported earnings. They conclude that analysts take into consideration previous change in earnings to conduct their analysis, thus turn to be optimistic and overestimate the change in earnings.

A further extended study is conducted by Capstaff, Paudyal and Rees (2001) covering 9 European countries including United Kingdom. Over 500,000 individual forecasts were observed from 1987 to 1994 in order to examine the error of analyst forecasts. Following the same methodology as Capstaff et. Al (1995), Capstaff et al (1995) results show that forecast accuracy differ among European countries, with Italy recording the highest mean error and Ireland the lowest. In their data analysis, they choose to study how the forecast error varies over the monthly horizons from -20 (20 months before fiscal year end) to +3 (3 months after fiscal year end). By doing this, they assume that most of the companies will release their reports 3 months after their fiscal year end by the latest.

2.2.6. Critical review, Rationale and Contributions of this Chapter:

According to the FCA (Financial Conduct Authority in the UK which complies with the Transparency Directive requirements set by the European commission in December 2004), companies have 120 days (4 months) from the time they close their books to the time they release their annual report. A lot of companies may also have exceptions to publish their results even later (*as is shown in our sample*). Prior to this regulation, companies had more flexibility and time in publishing results. The criteria used by Capstaff et al. (2001), and Capstaff et al. (1995) to observe the monthly horizons doesn't allow to cover the whole horizon, as it misses all the companies that publish their results later than 3 months of the announcement date. Given that companies' earnings release dates are different than the one another, fixing the announcement date to 3 months for all UK firms is inaccurate.

Similar to Capstaff et al. (2001), Becker, Steliaros and Thomson (2004) provide a study regarding the analyst forecast error in European countries but for a more recent sample period (1993-2002). Their main objective was "*to identify which (firm) characteristics, all else being equal, are associated with higher-than-average consensus earnings forecast error and bias. This information will benefit sell-side analysts by enabling them to identify which consensus estimates are more likely to be wrong. It will also help investment managers identify the companies that have a higher likelihood of being mispriced.*" (p. 77, Becker et al., 2004). The analysis also included the horizon effect from 24 month before earnings announcement date to 1 month before. Consistent with Capstaff et al. (2001), UK companies had the lowest forecast errors (1% forecast error one month before earnings announcement date).

Despite employing the announcement date as the end of the event window horizon, Becker et al. (2004) restrict their sample to firms that have a minimum market capitalisation of

$1Billion, a minimum 7 analyst followers per company where an analyst should be following the company for over 10 years, and furthermore, they limit the data to companies with December Fiscal year-end only. The final restriction is expected to exclude a large proportion of the listed companies (as shown later in table 2.3), thus the statistical population would not be fully representative since December fiscal year companies might have distinct characteristics from the rest of the companies. This chapter, however, utilises the full constituents of FTSE All Share regardless of their fiscal year end dates over a large period (1993 to 2013).

Das et al. (1998) as well restrict their sample to companies with fiscal year ending in December only. However, unlike Becker et al (2004), their financial analysts' observations cease at the Fiscal Year End rather than at the release date of the annual report which would vary substantially among firms[5] (see table 2.3). This would affect the results since financial analysts continue to forecast companies' earnings until the announcement date and not until the companies close their books. Hence, setting the last month of the horizon to the fiscal year-end would result in the period between the last forecast embedded and the published date being uneven across firms. This approach has two adverse effects on the consequent results. First, the information of the company's earnings would continue to flow throughout the horizon until the publish date. On average, the fiscal year-end month for one firm would reflect more information about its earnings if its announcement date sooner than for a firm with a delayed announcement date. Thus, forecast analysts' errors over the fiscal year-end-month are disparate and are not comparable. Second, forecast error is expected to decline as more information is released and hence, disregarding the period between the fiscal year-end and the announcement date will not reflect analysts' continual revisions prior to the announcement date.

Prior to these studies, the same criterion had been done by Easterwood and Nutt (1999) who top their observations at the date of fiscal-year end. However, it is important to note that Easterwood and Nutt (1999) start observing the analyst forecasts 4 months after last year's fiscal year-end as such forecasts could be associated with the previous year's earnings if they were not announced, and to ensure that analysts have had the previous realised earnings in hand to include it in their future forecasts. What is more interesting is that different companies have different fiscal year end and also different announcement

[5] Eams and Glover (2003) re-examined the work of Das et al. (1998) using a similar sample to study the association between earnings forecast errors and earnings predictability.

dates which could differ from the fixed four months period employed in their study. The same approach is also followed by Ackert and Athanassakos (2003) in their application of simultaneous equations model from 1981 to 1996.

Larocque (2013) also use December fiscal year ending firms to relate forecast errors with cost of capital equity estimates. Similar to Easterwood and Nutt (1999), Larocque (2013) too ignore the first four months of each calendar year assuming that the previous annual report wouldn't have been released yet.

In the same manner, the limitation of taking only December fiscal year ending companies was pointed out by Ali et al. (1992). In their study, all companies in New York Stock Exchange are taken with at least three consecutive years of data for realised and forecasted earnings per share. Ali et al., (1992) state: "*We do not limit our sample on the basis of listing status and/or December fiscal year-end month. Retaining OTC firms allows for the inclusion of smaller firms including firms with non-December fiscal year-ends produces a sample with a broader number of industries (Smith and Pourciau, 1988)*". However, similar to Easterwood and Nutt (1999), Ali et al (1992) stop observing the forecast errors at fiscal year-end rather than earnings announcement date. Additionally, they also skip the first four months after the fiscal year end.

An equally critical issue is the treatment of outliers in the dataset of forecasts which has always been considered a very important part in testing the bias of analyst forecasts, as it could lead to irrelevant results if wasn't treated correctly. Capstaff et al. (1995), Easterwood and Nutt (1999), Ali et al. (1992) and many other scholars shed the light on this issue by eliminating forecast error ratio is higher than 1. Despite the importance of this step to prevent the results from being driven by outliers, there is always a possibility that figures deleted could be genuine meaning real mistakes were made by analysts. Capstaff et al. (2001) treat the unusual figures carefully and eliminate the outliers at 4 different levels (100%, 200%, 300% and 400%).

In addition, they compare the results after elimination with the original results without elimination.

Guedj and Bouchaud (2005) study the bias of earnings forecasts in addition to its herding effect in the US, EU and Uk. Their paper covers in details 12 months' horizons before the earnings announcement dates. Nonetheless, the authors study 302 UK companies from 1987 to 2004. Those 302 fixed firms were always available in the UK stock market between 1987 and 2004. Nonetheless, having this fixed number of companies during 17 years damage the robustness of the study as it doesn't take into account the survivorship effect. These companies are the biggest, strongest and most stable to survive all this period. DeBondt and Thaler (1990) had previously criticised this matter.

For all that, this research will try to re-examine the UK analyst forecast rationality and bias, for FTSE all share companies from 1993 to 2013. The data will be better organised, giving insight information month by month before the earnings announcement date regardless of the Fiscal year End. The companies will be selected according to each year's specific number of public companies at the time of the observation. This is considered as an important contribution to the literature as the companies were collected handily year by year from 1993 to 2013. Selecting all the companies year per year will include all types of companies (all sizes and industries…), therefore is expected to reflect the true image of forecast bias of FTSE all share companies together regardless how big are they or how long they survived. In spite of that, size and industries are taken into consideration afterward. The impact of horizons and time on the forecast accuracy will be uncovered. In the end, the rationality of the analyst forecasts will be investigated.

Consequently, the following hypothesis questions could be drawn:

Hypothesis 2.1. Financial analysts are inaccurate when forecasting the fiscal year-end earnings of FTSE all share companies

Hypothesis 2.2. In case of any significant Error, financial analysts are irrational when making errors in forecasting companies' performance.

The aim of this research is to help investors make the best decision when considering the set of information available to them, one of which analysts' forecasts. A big problem arises when analysts become biased to their own benefits. Sell side analysts might have the incentives to issue optimistic forecasts to motivate investors to buy the analysed stock. Another problem appears when the relationship between managers and analysts affects earnings forecasts. Additionally, the existence of these abnormal scenarios may harm the efficiency of the market and increase the market imperfection.

2.3. Sample Selection and Firms' distribution

The data are collected for FTSE all share constituents from January 1993 to December 2013. The financial reporting standard 3 "FRS3" was introduced in the UK in June 1992, therefore observations in this research start from January 1993 in order to ensure that all companies have adopted the FRS3 into their reports. Regarding the information content of this new standard, Acker et al. (2002) explains that "*UK companies are required to provide more details in the income statement, distinguishing between continuing, discontinued and acquired operations. The income statement must also identify gains and losses on the sale or termination of an operation, the costs of fundamental organisation or restructuring, and gains and losses on the disposal of fixed assets (…) Furthermore, the Earnings per share must now be calculated after taking account of all unusual items, extraordinary and exceptional, whereas under SSAP3 extraordinary items were omitted from EPS*". (Acker et al., 2002).

Actual earnings per share (EPS), forecasted earnings per share and number of analyst forecasts all were collected from IBES database (Institutional Brokers Estimate System) available on Thomson Reuters. Consensus forecasts are monthly data and actual earnings are fiscal year-end reported earnings.

Companies listed in FTSE all Share were collected individually, reflecting the true number of companies listed in each year of the sample period. This is important since number of listed companies will vary from year to year due to mergers, acquisitions, new entrants or companies leaving the index.

Table 2.1 shows the distribution of FTSE all share companies per year. With an average of 746 firms per year, the highest number of companies listed in FTSE all share was in 1995 with 903 companies, whereas the lowest was in 2013 with 603 listed companies. Around 21% of those listed companies were excluded due to unavailability of data, leaving the sample with an average of 589 firms per year. The highest number of companies available for this study was in 1997 (727 companies) and the lowest was in 2013 with 438 available companies. Including all the companies in the analysis was essential to investigate the overall variation of forecast error in London stock exchange.

Table 2.1 Distribution of total number of firms listed in FTSE all share index, available firms for this study and analysts' forecasts in years.

year	Total number of firms listed	Available Firms	available analyst forecasts
1993	806	625	57751
1994	862	667	60649
1995	903	711	60408
1996	902	718	61624
1997	896	727	62878
1998	896	726	62413
1999	840	686	64349
2000	814	656	53555
2001	772	614	32635
2002	726	588	35958
2003	702	573	37133
2004	702	574	42636
2005	706	580	46279
2006	685	551	42905
2007	694	545	46458
2008	674	524	49239
2009	616	468	50324
2010	623	470	54644
2011	627	470	60169
2012	622	456	60226
2013	603	438	57508
average	746	589	52,369
total	15,671	12,367	1,099,741

By doing this, the index itself is being under investigation regardless the individual constituents. Moreover, survivorship effect of big companies is being avoided. A total of 12,367 firm-years that have 1,099,741 analyst forecasts over the 21 year sample period is analysed in this study. It's well known that analysts keep on forecasting earnings until the earnings actual release date and not when companies close their accounts. Consequently, monthly earnings' forecasts are studied in this research up until results are announced each year. In other words, earnings per share forecasts targeting the next fiscal year are observed monthly from 11 to 1 month prior to earnings announcement date.

However, forecasts collected are monthly average and earnings announcement date might fall in the middle of a month, meaning that the first month should be eliminated since it contains mixed data belonging to current and previous fiscal year. Companies with less than 3 analyst forecasts per month were also eliminated. Table 2.2 shows the distribution of firms and analyst forecasts calculated for each horizon over the period of study (from 11 to 1 month prior to announcement date each year). A total of 12,814 firms per horizon during 20 years with over one million analyst forecasts were available for this study. It's worth mentioning that although managing and organising such a big sample is always tricky and complicated, however, it is always considered as an advantage in favour of any panel data analysis.

Table 2.2 Distribution of firms and analysts' forecasts in monthly horizons during 20 years (from 11 to 1 month prior to earnings release date).

Month-horizon	number of firms available	number of forecasts
11	12,814	98,038
10	12,814	98,995
9	12,814	99,708
8	12,814	99,959
7	12,814	99,917
6	12,814	100,309
5	12,814	100,738
4	12,814	100,328
3	12,814	100,416
2	12,814	100,522
1	12,814	99,899
average	12,814	99,894
total		1,098,829

In order to discover how long each company takes to release its financial figures, the “End of Fiscal year” and “Date of announcement of financial reports” are collected from Worldscope database using Datastream Thomson Reuters. According to the financial conduct authority in the UK (FCA) (2015), “An *issuer* must make public its annual financial report at the latest four months after the end of each financial year”.

Table 2.3 shows the distribution of companies according to their fiscal year end, earnings release month and how long it takes them to release their reports. d Moreover, to comply with FCA rules most companies release their report within 3 months after the fiscal year end (87%). This still leaves us with 1,694 companies taking more than 3 months to release their reports. In contrast to studies that ignored the first few months (Ali et al (1992), Capstaff et al (2001), Capstaff et al. (1995), Easterwood and Nutt (1999) and more), results in the UK show that not all companies announce their results to public within 4 months. While 3.1% of companies released within 1 month, it took 34% of them 2 months to announce their earnings.

2.4. Data Analysis:

2.4.1. Forecast Bias and Forecast error:

Two measures of forecast error were used in this study:

$$\mathbf{1.}\ \boldsymbol{FE_{ihT} = \frac{F_{iht} - E_{it}}{|E_{it}|}}$$

Forecast Bias: this is the traditional approach which is equal to the difference between Actual earnings per share and forecasted earnings per share divided by the absolute value of actual earnings per share. This first measure will help showing the sign of forecast error meaning in which direction the bias went. Where $\boldsymbol{FE_{ihT}}$ is forecast error made in horizon h for year t and firm I; $\boldsymbol{F_{iht}}$ is the EPS forecast in monthly horizon h for year ending t and firm I; $\boldsymbol{E_{it}}$ is the actual EPS for firm i at year t; “h” is the monthly distance (11 to 1 horizon) from which the forecast was made until earnings announcement date.

Table 2.3 Distribution of Firms according to the month in which their fiscal year ends, the month in which they release their annual report and the number of months they take until they release the annual report.

Distribution of Firms according to their month of fiscal year end			firms distribution according to their Earnings release month of the year			Firms distribution according to number of months a company takes to announce its earnings after its fiscal year ends		
Month Fiscal year end	**N. Firms**	**percentage**	**Month Fiscal year end**	**N. Firms**	**percentage**	**N. of months**	**N. Firms**	**percentage**
Jan	788	5.1%	**Jan**	326	2.2%	**0**	56	0.4%
Feb	306	2.0%	**Feb**	1900	12.6%	**1**	471	3.1%
Mar	2975	19.2%	**Mar**	4279	28.4%	**2**	5213	34.6%
Apr	834	5.4%	**Apr**	1108	7.3%	**3**	7612	50.6%
May	344	2.2%	**May**	1518	10.1%	**4**	1392	9.3%
Jun	1061	6.9%	**Jun**	1846	12.2%	**5**	188	1.2%
Jul	366	2.4%	**Jul**	832	5.5%	**6**	53	0.4%
Aug	348	2.3%	**Aug**	249	1.7%	**7**	37	0.2%
Sep	1322	8.5%	**Sep**	916	6.1%	**8**	11	0.1%
Oct	363	2.3%	**Oct**	547	3.6%	**9**	5	0.0%
Nov	187	1.2%	**Nov**	866	5.7%	**10**	6	0.0%
Dec	6571	42.5%	**Dec**	689	4.6%	**11**	2	0.0%
Total	**15465**	**100%**	**Total**	**15076**	**100%**	**Total**	**15046**	**100%**

$$2.\ |FE_{ht}| = \left|\frac{F_{iht} - E_{it}}{E_{it}}\right|$$

Forecast Error: The second measure is the total absolute value of EPS forecasts minus realised EPS over realised EPS. In this measure, the sign of the deviation is of no importance but will only help to see the magnitude of the error.

Observations for which earnings per share is less than 5 pence were excluded because FE cannot be defined when EPS is 0, and small values of EPS can result in extreme values in FE thus influencing the result**.** Following Capstaff et al. (2001), data were trimmed in order to prevent outliers from deteriorating the result. Forecast errors higher than 400%, 300%, and 200% were eliminated once at a time. However, initial untrimmed figures were also included in the analysis to allow for comparison.

Using equation 1 of forecast error, table 2.4 shows how the absolute value of Forecast error was changing across the months prior to earnings announcement. As expected, forecast accuracy improved as time approached the announcement date and this was demonstrated as error decreased from 22.1% to 16% from month 11 to 1 month respectively prior to earnings announcement date. The Trimming criteria of minimum 400%, 300% and 200% didn't make a big difference when compared to the original figures suggesting there could be limited number of outliers in the dataset.

The other measure of forecast bias is illustrated in Figure 2.1 to indicate the sign or direction of analyst forecast bias and to capture their behavioural intentions. It should be noted that *figure 2.1* results are different than the ones in table 2.4 since figure 2.1 uses the normal forecast bias formula and not its absolute value. The graph shows a clear positive bias meaning that monthly mean forecast is greater than actual earnings. In theory, this difference could be explained by the optimistic behaviour of forecasters towards the firms they are targeting. Albeit this bias significantly shrinks as analysts approach the end of each year which is normal as less information is known at the beginning of a fiscal year.

Table 2.4 Analyst Forecast Error 11 to 1 month prior to earnings announcement date, Trimmed at 400%, 300% and 200%. $|\mathrm{FE_{ht}}| = \left|\frac{\mathrm{F_{ht}-E_t}}{\mathrm{E_t}}\right|$. Where FE_{ihT} is forecast error made in horizon h for year t and firm I; F_{iht} is the EPS forecast in monthly horizon h for year ending t and firm I; E_{it} is the actual EPS for firm i at year t; "h" is the monthly distance (11 to 1 horizon) from which the forecast was made until earnings announcement date.

Horizon	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
NO Trimming	22.1%	21.1	20.4	19.7	18.7	17.9	17.2	16.6	16.3	16.0	16.0
Trimming 400%	21.7%	20.9	20.1	19.5	18.6	17.8	17.1	16.5	16.1	15.9	15.9
Trimming 300%	21.0%	20.2	19.7	19.1	18.3	17.4	16.7	16.2	15.9	15.7	15.6
Trimming 200%	20.0%	19.5	18.7	18.1	17.4	16.7	16.1	15.7	15.4	15.2	15.1

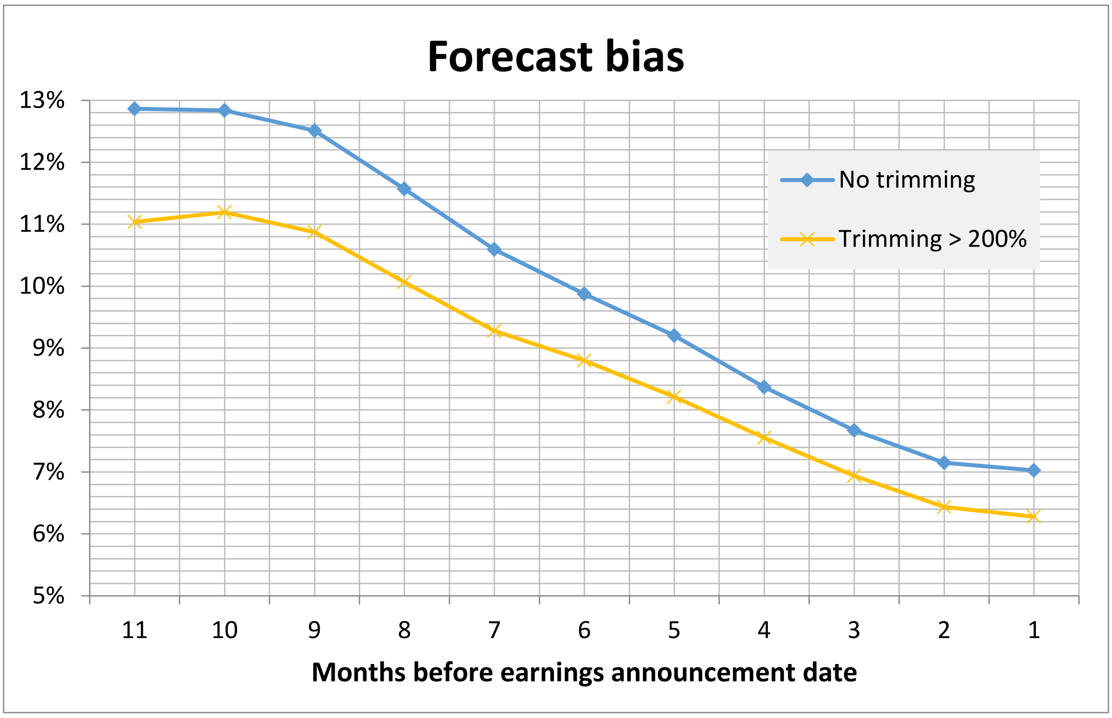
2.4.2. Weighted Average yearly forecasts:

Since forecasted earnings are sensitively affected by any new information, private or public, it is normal to deduce that analysts conducting a forecast at the end of the year have an advantage over the ones doing it at the beginning of the year since they have more information in hand. Therefore, it was unfair to treat all monthly forecasts equally.

Instead of calculating the normal arithmetic average, weighted average of monthly earnings forecast is used depending on the distance of each month to the end of the fiscal year. Hence, a weight of 1 will be given to the first month of the year and 12 to the last month just before earnings are announced. Weighted averages as well as normal averages are used in regressions where yearly forecasts are needed.

Figure 2.1 Forecast Bias from 11 to 1 month prior to earnings release date.

$FE_{hT} = \frac{F_{ht}-E_t}{|E_t|}$. Where FE_{ihT} is forecast error made in horizon h for year t and firm I; F_{iht} is the EPS forecast in monthly horizon h for year ending t and firm I; E_{it} is the actual EPS for



firm i at year t; "h" is the monthly distance (11 to 1 horizon) from which the forecast was made until earnings announcement date.

2.4.3. How Significant Analysts' forecast errors are?

So far preliminary results were being discussed without being placed under statistical verification. In this section different statistical regressions will be used in order to check whether analysts' forecast errors are significant or not. De Bondt and Thaler (1990) studied the issue by regressing actual change in earnings per share over the change in forecasted earnings per share. This study follows De Bondt and Thaler (1990) to test how big and how significant yearly mean forecast errors are. Since individual effect was heavily present in the data, the use of fixed effect regression analysis was essential to take into account companies' individual characteristics. The following regression will test the size and direction of analysts' forecast error. Data were clustered by individual companies to take into account heteroskedasticity and serial correlation problems.

3. $\boldsymbol{AC_{it} = \alpha_i + \beta\, FC_{iht} + \varepsilon_{it}}$

$$\boldsymbol{AC_{\ it} = \frac{EPS_{it} \ - \ EPS_{it-1}}{EPS_{t-1}}}$$

$$\boldsymbol{FC_{it} = \frac{F_{ith} - EPS_{it-1}}{EPS_{it-1}}} \ .$$

Where AC_{it} is the actual change in EPS from t-1 to t; FC_{iht}, the forecast change, measures the deviation of the forecast in year t at horizon h from the previous earnings per share; α_i is the mean forecast error; and β determines the sensitivity of analysts' reaction to available information at the time of forecast. The regression estimates the analysts' reaction per each horizon month h in the event window. However, when regressing yearly average or weighted yearly average, the horizon h is dropped out as FC_{it} indicates annual forecast change instead. De Bondt and Thaler (1990) used cross sectional data in their analysis consisting of forecasts made in April of each year. They ran a regression for each year and presented a pooled sample. In this study, however, panel data is used including monthly forecasts and yearly earnings per share in order to check the horizon effect on forecast accuracy.

The null hypothesis could be drawn as for an excellent analyst with 100% forecast accuracy, α should to be 0 and β equal to 1. The interpretation of this regression could be made as follow: α will determine the size of forecast error and its sign will indicate the direction of bias. Thus If α is negative, analyst forecast is overall optimistic since earnings forecast is bigger than actual earnings. A positive α means analyst forecasts are pessimistic.

A combined explanation of parameters β and α would give a clearer image. In case α is negative and β is less than 1, analyst forecasts are considered optimistic and overreacting to available information regarding actual earnings. Assuming α is negative and β being bigger than 1, this will mean analysts are still optimistic but with a sense of underreaction.

Table 2.5 exhibits the results of the fixed effect regressions. Panel A reports the results for the whole sample and shows that analysts are optimistic when it comes to forecasting, however, not as extreme as the literature claims (DeBondt and Thaler (1990), Capstaff et al. (2001)). Throughout the whole period, α is statistically negative and it increases monotonically from -14.7% in event month h-11 to -7.7% in event month h-1 indicating that the forecast error is reduced towards the earnings announcement date. On the other hand, β decreases from 1.008 to 0.897 monotonically over the same horizon. The results indicate that analysts were optimistic, however there seems to be no significant sign of over- or underreaction to available information since β is not substantially far from 1. All results were statistically significant at 1% confidence level. Panel B reports the results for the trimmed sample by removing outliers (deleting Forecast errors of more than 200%). The findings are similar to the whole sample.

Despite consistency in the findings of this chapter with the literature regarding the optimism of forecasters, the results show some disparity in the magnitude of forecast bias among previous studies. For instance, Capstaff et al (1995) report a yearly average forecast error of 16% and last month's error of 10% compared to 11.2% and 7.7% in this study, respectively. The difference could be due to the fact that this study employs precise earnings announcement dates as opposed to the fixed three months period following fiscal year end used by Capstaff et al (1995). Contrarily, Guedj and Bouchaud (2005) report very low forecast errors using a sample of only surviving public companies. This study however, doesn't suffer from survivorship effect hence the forecast error appears to be higher since all available companies were included.

As suggested in section 2.4, the Transparency Directive requirements were changed in December 2004 asking "the issuers of securities traded on regulated markets within the EU to make their activities transparent, by regularly publishing certain information" (The transparency directive 2004/109/EC).

The information to be published includes:

- yearly and half-yearly financial reports
- major changes in the holding of voting rights
- ad hoc inside information which could affect the price of securities

This information must be released in a manner that benefits all investors equally across Europe including the UK. Further analysis was applied to see if this change had impacted the way analysts perform in terms of forecasting earnings per share. Results of this analysis are added to appendix 8. Where the forecast errors remain statistically significant after the change, there appear a slight decrease in the values of these errors on monthly basis. However, this marginal decrease wasn't a significant one.

2.4.4. How Rational/Transparent financial analysts are?

One sort of forecast irrationality is when analysts' forecasts become biased and predictable. For example, if a forecaster's analysis was easily predicted then one could conclude that analysts are following a certain trend and they are not transparent.

In a perfect world, analysts should rely on a set of information analysed in a rational way and issued differently from time to time without following a specific trend. Nonetheless, previous findings suggested that forecast revisions could be predicted using the first forecast of the year. De Bont and Thaler (1990) raised two clear questions to test the issue of analyst rationality: "The first is whether forecast errors in EPS are systematically linked to forecasted changes. In particular, are the forecasts too extreme? Are most forecast revisions "up" or "down" if the analysts initially projected large declines or rises in EPS? Clearly, under rationality, neither forecast errors nor forecast revisions should ever be predictable from forecasted changes. The second question is whether the bias in the forecasts gets stronger as uncertainty grown and less is known about future?"

Table 2.5 Regression analysis of actual change on forecast change at different horizons. Regression analysis showing Analyst Forecast Bias from 11 to 1 month prior to earnings announcement date, including yearly average and yearly weighted average. Original regression results are shown in addition to results after deleting forecast errors which are greater than 200% (considered as outliers). $AC_{it} = \alpha_i + \beta\ FC_{iht} + \varepsilon_{it}$. ***Where*** AC_{it} ***is the actual change in EPS from t-1 to t;*** FC_{iht}***, the forecast change, measures the deviation of the forecast in year t at horizon h from the previous earnings per share***

	Original data- No trimming				Trimming FE>200%				
Monthly horizons (h)	**β (t-statistics)**	**α (t-statistics)**	**n. obs**	**R-squared**	**β (t-statistics)**	**α (t-statistics)**	**n. obs**	**R-squared**	**N. of forecasts**
11	1.008***	-0.147***	6,452	0.934	1.033***	-0.120***	6,366	0.955	98982
	(38.51)	(-17.50)			(40.84)	(-16.24)			
10	1.006***	-0.141***	6,475	0.941	1.029***	-0.117***	6,398	0.961	99695
	(40.30)	(-17.54)			(42.36)	(-16.25)			
9	0.993***	-0.139***	6,502	0.946	1.014***	-0.114***	6,427	0.965	99947
	(42.91)	(-18.81)			(41.76)	(-16.10)			
8	0.992***	-0.132***	6,496	0.950	1.013***	-0.107***	6,424	0.969	99904
	(46.14)	(-19.60)			(45.69)	(-16.89)			
7	0.987***	-0.130***	6,494	0.949	1.009***	-0.106***	6,427	0.969	100297
	(42.35)	(-17.89)			(47.80)	(-17.68)			
6	0.963***	-0.117***	6,521	0.936	1.001***	-0.0995***	6,458	0.968	100725
	(28.04)	(-10.83)			(47.07)	(-16.30)			
5	0.949***	-0.109***	6,516	0.946	0.987***	-0.0940***	6,455	0.978	100314
	(24.14)	(-8.997)			(94.16)	(-31.62)			
4	0.939***	-0.101***	6,507	0.948	0.975***	-0.0864***	6,452	0.979	100401
	(25.72)	(-9.157)			(101.4)	(-32.44)			
3	0.932***	-0.0946***	6,499	0.952	0.965***	-0.0790***	6,445	0.980	100505
	(27.77)	(-9.434)			(95.74)	(-28.65)			
2	0.906***	-0.0849***	6,462	0.950	0.941***	-0.0709***	6,411	0.981	99883
	(25.09)	(-7.984)			(110.5)	(-30.95)			
1	0.897***	-0.0779***	6,435	0.949	0.934***	-0.0657***	6,383	0.983	98946
	(24.66)	(-7.394)			(139.7)	(-37.02)			
Average	0.958***	-0.112***	6,482	0.944	0.997***	-0.0939***	6,385	0.978	99963
	(28.04)	(-16.42)			(52.83)	(-18.12)			
weighted average	0.943***	-0.102***	6,472	0.948	0.981***	-0.0833***	6,389	0.980	99914
	(24.14)	(-15.33)			(69.55)	(-22.71)			
t-stat in parentheses	*** p<0.01, ** p<0.05, * p<0.1								

Following DeBont and Thaler (1990), the regression could be written accordingly:

$$\mathbf{4.}\ \boldsymbol{Forecast\ Revision_{th} = \alpha + \beta\ Forecast\ Change_{th} + \varepsilon_t}$$

$$FR_{it} = F_{it12} - F_{it1}$$

$$FC_{it} = F_{it1} - EPS_{it-1}$$

Where Forecast Revision FR_{it} is the difference between mean forecasts made at the last month before announcement date, and the first one after previous announcement was made. Forecast change FC_{it} is the difference between mean forecasts F_{it1} made in the first month just after the previous announcement for year t was made, and the last reported earnings per share EPS_{it-1}. It is good to note that De Bont and Thaler (1990) used the difference between December and April forecasts (8 months horizon revision). This study, however, covers all companies which have different fiscal years without exception. Rationality consists that β should be equal to 0. If β is negative this means that forecasts are going downwards after the first forecast. A positive β implies that forecasts are going upwards after the first forecast of the year.

Results regarding regression 4 appear in Table 2.6 including total data, positive forecast change and negative forecast change. In general, after regressing revisions made at the end of the year with prior forecasts made at the beginning of the year, a negative effect of -9.71% carried by the first month forecast change appears to be statistically significant at 1% confidence level. However, this effect was not as strong as the coefficients shown in DeBondt and Thaler (1990) and Capstaff et al. (1995). In comparison with DeBondt and Thaler (1990), the same monthly horizons were applied in this test to allow for comparison after they chose to use fiscal year end instead of announcement date as an ending point. Results of negative effect remained present but slightly lower by 0.8% and this is normal since the last 4 months before the announcement date were excluded by DeBondt and Thaler (1990). Additionally, it was necessary to separate forecast changes by positive and negative in order to see how an optimistic or pessimistic the change in first forecast would affect following revisions. An optimistic change in forecast means that the first forecast after the previous announcement was higher than the previous EPS, signalling positive expectations regarding company's future earnings. A negative change in forecast would mean a lower earnings forecast than the previous year earnings (yet it doesn't have to be losses). Regarding positive forecast changes, β was clearly negative and statistically significant at 1% confidence level. However, negative forecast changes had no significance in terms of affecting future revisions.

Table 2.6 **Regression analysis showing whether Analyst Forecast changes could predict the following forecast revisions. Two revision dates/horizons were used in this regression: revisions made the last month before the announcement date where previous forecast was made at the beginning just after the previous announcement date; and Debont and Thaler (1990) who used revisions made just before the end of fiscal year where previous forecasts were made 4 months after the end of previous fiscal year.[** $\boldsymbol{Forecast\ Revision_{th} = \alpha + \beta\ Forecast\ Change_{th} + \varepsilon_t}$**]**

horizon	β (t-statistics)	α (t-statistics)	n. of observations	R-Squared
all				
forecast made by horizon 0 , prior forecast at horizon 11 prior to announcement date	-0.0971*** (-7.694)	-0.0171 (-1.586)	6,956	0.378
Debont and Thaler: revisions made at horizon 0, prior forecast at horizon 8 of FY end	-0.105*** (-9.556)	0.0135 (1.448)	7,052	0.477
Positive Forecast Change				
revisions made by horizon 0, previous forecast at horizon 11 prior to announcement date	-0.0979*** (-8.298)	-0.00498 (-0.381)	5,541	0.387
Debont and Thaler: revisions made at horizon 0, prior forecast at horizon 8 of FY end	-0.106*** (-10.28)	0.0311*** (2.735)	5,635	0.485
Negative Forecast Change				
forecast made by horizon 0, previous forecast at horizon 11 prior to announcement date	0.162 (0.728)	-0.00279 (-0.0541)	1,415	0.010
Debont and Thaler: revisions made at horizon 0, prior forecast at horizon 8 of FY end	0.0950 (0.578)	-0.00783 (-0.205)	1,417	0.005

Nevertheless, the full story wouldn't be complete without looking at the number of observations for each case. Unsurprisingly, positive forecast changes occupied 80% (5541 out of 6956) of the total pooled observations and in only 20% of the cases forecasters predicted lower future earnings compared to previous earnings. With β being significantly negative, it is not just that analysts seem to be optimistic as confirmed in previous regressions, but they also tend to revise their forecasts downwards by around -9,71% from the beginning until the announcement date.

An interesting factor in this result is that the forecast remains above the actual earnings released in the last month of forecast, even with a steady downward revision throughout the previous months. This result contradicts with previous studies suggesting that managers try to convince analysts to walk down their forecasts in order to generate a positive surprise by the end of the year. The theory of realised earnings meeting or beating the analysts' forecasts cannot be confirmed in this chapter.

All in all, it is possible to claim that the sign of analysts' revisions could be predicted using their first forecast deviation from previous EPS. Consequently, the null hypothesis of rational analysts is rejected when forecast changes are positive compared to previous earnings which occurred in 80% of the cases for FTSE all share companies during 21 years.

2.4.5. Incorporating past earnings in financial forecasts:

So far one form of irrationality of financial analysts has been discussed in this study and this is systematic bias in earnings' forecasts. Nonetheless, another sort of irrationality was mentioned in the literature is when average forecasts systematically miss-react to the release of past year's earnings. In other words, systematic underreaction or overreaction to past year's earnings is considered as a mistreatment of information and therefore defined as irrational behaviour that could lead to serious trouble in financial markets. According to Easterwood and Nutt (1999), "if markets treat analysts' forecasts as both rational and statistically optimal, then inefficient forecasts could have important implications for the efficiency of pricing in securities markets".

A formal test proposed by Abarbanell and Lehavy (1992) investigates whether forecast errors are characterised by overreaction or underreaction to prior change in realised earnings.

$$5. EPS_{it} - F_{iht} = \alpha_i + \beta[EPS_{it-1} - EPS_{it-2}] + \epsilon_{it}$$

Where the dependent is the inverse of forecast error, EPS_{it}, EPS_{it-1} and EPS_{it-2} are the actual earnings per share at time t , t-1 and t-2 respectively; F_{iht} is the earnings forecast for year t and done at horizon h; ϵ_{it} is the disturbance term. If F_{iht} is efficient enough, β will be equal to 0. In this case, no relationship between forecast errors and prior year change in earnings should be found. An overreaction of forecast will be reflected in a negative β and underreaction means β should be positive.

Contrary to Easterwood and Nutt (1999) and Abarbanell and Lehavy (1992), Table 2.7 confirms that no relationship was found between forecast error and growth in prior year earnings as β was almost 0 in all horizons and statistically non-significant in all quarters. Although forecasts were found to be generally optimistic as discovered earlier using regression 3, table 2.7 shows that such bias couldn't be described as an overreaction to prior earnings change. This overreaction, however, could still be affected and explained by other source of information but not particularly by prior year earnings.

Table 2.7 Regression analysis 5 of forecast error inverse at the first month just after the previous year earnings were announced and before the end of each quarter. In addition, yearly average and weighted yearly average forecast were also used as dependent factors. $\mathbf{EPS_{it} - F_{iht} = \alpha_i + \beta[EPS_{it-1} - EPS_{it-2}] + \epsilon_{it}}$

TIME OF forecast	β (t-statistics)	α (t-statistics)	n. of observations	R-Squared	N. of Companies
1 month after prior year announcement	0.000458	-0.159***	5,698	0.000	853
	(0.377)	(-647.8)			
before first quarter	-0.000100	-0.152***	5,704	0.000	854
	(-0.0925)	(-698.5)			
before second quarter	0.000887	-0.128***	5,719	0.000	855
	(0.678)	(-478.5)			
before third quarter	0.000420	-0.101***	5,714	0.000	856
	(0.296)	(-346.7)			
before announcement date	0.000463	-0.0826***	5,650	0.000	848
	(0.310)	(-257.4)			
Average	0.000647	-0.117***	5,661	0.000	846
	(0.530)	(-443.2)			
weighted average	0.000693	-0.106***	5,658	0.000	846
	(0.504)	(-357.0)			
t-stat in parentheses	*** p<0.01, ** p<0.05, * p<0.1				

2.4.6. Robustness check: re-estimating the forecast rationality using closing-year-end as the end date of forecasts and using December-year-end firms:

To study the rationality of forecasts during a fiscal year it was necessary to take the full length of yearly window forecasts from the beginning of the year up until the earnings reporting date. However, to allow for comparison with previous studies and to further highlight the limitations in the literature, the forecast rationality is re-estimated in this section as a robustness check using two different sampling methods.

The first one is by including the forecasts from the beginning of the year until the fiscal year end rather than the earnings announcement date. As highlighted in section 2.2.6, this method was adopted by many studies including Das et al. (1998), Easterwood and Nutt (1999) and Larocque (2013). The main limitation of this method is that it ignores the fact that analysts continue to forecast companies' earnings until the earnings announcement date rather than the fiscal year end. Moreover, when taking the yearly average of consensus forecast error, their results would've overlooked the months of most accurate forecasts (usually the last few months before the earnings announcement date as shown in figure 2.1).

Table 2.8 shows the result after applying the same regression analysis as regression n.4, with the only difference being using fiscal year end as the last point for the forecast rather than the announcement date. Another limitation could be highlighted is that the literature often overlooks the first 3 months of the year, to allow the analysts to have learned about the previous reported earnings in order to implement them in their following forecasts. This can be seen in average2 where the average of all forecast change horizons are taken excluding the first 3 months of the fiscal year.

Table 2.8 shows the same downward trend in the forecast error compared to the previous analysis results. This is expected since the forecasts used are the same in essence but with difference in the beginning and end of the windows, and forecasts usually get more accurate the closer they get to the announcement date or fiscal year end. The main difference between the original sample and this robustness sample is the overall accuracy. Ignoring the last few months before the announcement date increased the overall average of error from 11.2% to 12.8% as can be seen in average 1. Comparing these two numbers might show a small difference of 1.6%, however, this is logical since we're dealing with averages of 11 horizons.

Table 2.8 Regression analysis of actual change on forecast change at different horizons. Regression analysis showing Analyst Forecast Bias from 11 to 1 month prior to fiscal year end, including yearly average. $AC_{it} = \alpha_i + \beta\, FC_{iht} + \varepsilon_{it}$. ***Where AC_{it} is the actual change in EPS from t-1 to t; FC_{iht}, the forecast change, measures the deviation of the forecast in year t at horizon h from the previous earnings per share. Average1 is the average of all horizons of forecast change. Average 2 is the average of all horizons of forecast change excluding the first 3 months of the fiscal year.***

horizons per month	β (t-statistics)	α (t-statistics)	n. observations	R-squared
11	1.009***	-0.146***	6408	0.934
	(38.74)	(-17.61)		
10	1.006***	-0.140***	6431	0.941
	(40.52)	(-17.64)		
9	0.993***	-0.137***	6,457	0.947
	(43.07)	(-18.89)		
8	0.993***	-0.131***	6,450	0.951
	(46.36)	(-19.66)		
7	0.988***	-0.128***	6,442	0.950
	(42.67)	(-18.00)		
6	0.963***	-0.116***	6,457	0.937
	(28.27)	(-10.88)		
5	0.950***	-0.118***	6,416	0.947
	(24.86)	(-9.227)		
4	0.942***	-0.111***	6,089	0.951
	(27.23)	(-9.691)		
3	0.962***	-0.1089***	6121	0.983
	(24.86)	(-9.131)		
2	1.010***	-0.105***	6231	0.923
	(25.76)	(-8.312)		
1	0.676***	-0.101***	6009	0.914
	(22.76)	(-7.922)		
Average 1	0.968***	-0.128***	6,408	0.949
	(28.92)	(-11.42)		
Average2	0.942***	-0.109***	6,408	0.921
	(28.43)	(-11.14)		
t-stat in parentheses	*** p<0.01, ** p<0.05, * p<0.1			

The main difference can be seen when comparing the forecast error in last month before fiscal year end and the last month before the announcement date. In the original data, the most accurate monthly forecast appeared in the last month with 7.7% optimism. The robustness sample of fiscal year end shows that the last month forecast error is 10.1%. All results were statistically significant at 1% confidence level.

Such limitations in the sample can have cumulative effects where previous studies built their analysis and results based on it. Easterwood and Nutt (1999) for example report that analysts tend to underreact to abnormally negative news and overreact to abnormally positive ones. However, based on the reasons highlighted above, the consensus forecast error in their study is most probably being overrated (see section 2.2.6) leading to higher overreaction in optimistic forecasts.

The second robustness check is by including a sample of December fiscal year end firms only. In section 2.3 we reported that only 42.5% of the overall companies have their books closed in December (with the second most common month being March and the rest are scattered differently). Therefore, taking December fiscal year end only may not fully represent the index under investigation and might lead to sampling bias. Similarly to regression n.4, the same regression analysis was run but for a sample of firms with December fiscal year ending only and results are shown in table 2.9 below.

Results in table 2.9 show that analysts tend to be more accurate when forecasting companies with December fiscal year end than the average of the overall index. Despite not having a statistical significance of the last few months before the announcement date, the size of the error decreases to as low as 1% compared to 7% when taking all companies into account.

Having statistically insignificant averages might be due to the insignificance of the last 6 months. However, the small economical values of forecast error across all horizons (when taking December fiscal year only), is quite similar to what the literature reported for the UK (see Becker et al (2004), Larocque (2013), Das et al. (1998), among others). The general feeling in these studies is that analysts can perform as a strong proxy for market returns based on UK companies' performances through earnings per share. This could be misleading when taking into account the overall index.

The values generated from such restricted samples, however, are believed to be resulting in seriously misleading conclusions that are referenced across the literature from behavioural finance (DeBondt and Thaler (1990)), to asset pricing (Larocque (2013), Hribar and McInnis (2012)). Larocque (2013)'s motivation was to use the adjusted forecast error as a proxy for market expectation of future return. Similarly, Hribar and McInnis (2012) use forecast error as a proxy of future returns and find that it is positively significantly affecting stock returns and that the impact of sentiment index on cross-sectional returns has been overshadowed by the power of forecast optimism. Moreover, Capstaff et al (1995) suggest that the possible reasons behind analysts' inaccuracy are that analysts in some cases may not be motivated to maximise the accuracy, particularly when they have incentives to increase the volume of trade generated after their forecasts.

Table 2.9 Regression analysis of actual change on forecast change at different horizons applied only on firms with December fiscal year end. Regression analysis showing Analyst Forecast Bias from 11 to 1 month prior to earnings announcement date, including yearly average and weighted yearly average. $AC_{it} = \alpha_i + \beta\ FC_{iht} + \varepsilon_{it}$. ***Where*** AC_{it} ***is the actual change in EPS from t-1 to t;*** FC_{iht}, ***the forecast change, measures the deviation of the forecast in year t at horizon h from the previous earnings per share.***

horizons per month	β (t-statistics)	α (t-statistics)	n. obs	R-squared	% of Dec Firms	n. of firms
11	0.683***	-0.0770***	2,844	0.579	44%	422
	(6.883)	(-2.761)				
10	0.732***	-0.0789***	2,859	0.630	44%	422
	(8.019)	(-2.966)				
9	0.739***	-0.0773***	2,878	0.641	44%	423
	(8.376)	(-3.053)				
8	0.753***	-0.0758***	2,879	0.649	44%	423
	(8.882)	(-3.165)				
7	0.744***	-0.0698**	2,884	0.639	44%	422
	(9.088)	(-2.276)				
6	0.647***	-0.0416	2,896	0.629	44%	421
	(5.662)	(-1.187)				
5	0.577***	-0.0223	2,893	0.649	44%	423
	(5.938)	(-0.766)				
4	0.578***	-0.0176	2,885	0.652	44%	422
	(5.834)	(-0.613)				
3	0.576***	-0.0127	2,884	0.669	44%	423
	(6.153)	(-0.480)				
2	0.533***	0.000844	2,846	0.642	44%	421
	(6.243)	(0.0355)				
1	0.513***	0.0119	2,836	0.611	44%	421
	(6.035)	(0.519)				
Average	0.585***	-0.0247	2,858	0.611	44%	424
	(5.329)	(-0.759)				
weighted average	0.582***	-0.0180	2,853	0.636	44%	424
	(5.59)	(-0.60)				
t-stat in parentheses	*** p<0.01, ** p<0.05, * p<0.1					

The analysis and robustness estimations presented above show that every study has its own case and limitations. The main conclusion that could be drawn from this is that analysts' forecast cannot be looked at neither being extremely and purposefully optimistic, nor as accurate as they could form a strong proxy of future market performance, at least not on their own.

2.5. Conclusion:

The effort put by financial analysts to provide investors with accurate earnings forecasts cannot be considered genuinely transparent all the time. Even though the amount of public and insider information available to them nowadays is massive and rapidly delivered, personal benefits could tempt any human being to publish biased results. Many shortcomings in data management have been found in the literature, however, this research controls for them in order to conduct a better forecast error analysis. One of these drawbacks is setting the fiscal year-end date as the ending of the forecast period although analysts keep forecasting until the announcement date. Another drawback is employing a sample of firms with December fiscal year ending only. Such decisions are believed to be misrepresenting the consensus of analysts' forecast errors.

Using 21 years of monthly forecast consensus data, three types of regression analysis were used in order to investigate the rationality of financial analysts towards UK listed companies. The first analysis relates forecast change to actual change in order to observe how accurate financial analysts are, and if not, in which direction they are biased. Consequently, the literature's common point of "Analyst Optimism" was again found statistically significant in this chapter for UK analysts from 1993 until 2013. The second one tests whether forecast revisions could be predictable using the first forecast change. This will help proving whether analyst forecasts follow some specific trend all the time, which in turn would raise a big question mark regarding the transparency of analysts. Moreover, Forecasts' revisions were found to be predictable using the first forecast deviation but coefficients were lower than what is found in De Bondt and Thaler (1990), Capstaff et al. (1995) and Capstaff et al. (2001). However, after separating negative and positive forecast change, positive forecast changes appear to be the dominating force in predicting forecast revisions. This result is coherent with forecast optimism which is already been proved, making the number of positive forecast change much bigger than the negative ones (5541 to 1415). The last one examines if previous earnings change could lead to an overreaction of related future forecast. The findings couldn't prove any relationship between forecast error and previous year earnings. This is inconsistent with results in Abarbanell and Lehavy (1992) and Easterwood and Nutt (1999) who found significant relationship between previous year earnings change and forecast errors.

An up-to-date investigation carried out in this study provides a better understanding of the financial analysts' forecasting nature, precision and rationality. The optimistic bias of analysts doesn't seem to be fading away. However, inconsistent results cannot prove whether this imprecision in earnings forecasts can move analysts to the level of irrationality. Given the lack of a clear cut conclusion regarding this matter, a detailed investigation of the determinants of such error is needed, since analysts could also be the victims of external variables. Consequently, chapter two takes the debate even further by testing the different factors that might impact the forecast error.

Chapter 3:

Earnings Management and Analysts' forecasts

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Abstract

Financial analysts are believed to play a major role in driving financial markets. Any error or bias in financial analysts' forecasts is likely to mislead investors who rely on these forecasts to make big investment decisions. Furthermore, managers are thought to be manipulating earnings in order to meet or beat analysts' forecasts and such manipulation would make it harder for analysts to accurately forecast earnings, resulting in higher Forecast Errors. While academics focused mainly on the incentives that push managers to manage earnings including analysts' forecast, they missed the fact that this impact could've originally been reversed. This chapter investigates the relationship between Analysts' Forecast Error and Earnings management based on abnormal accruals and real activities, by analysing FTSE all share companies in London Stock Exchange from 1993 to 2013.

Preliminary results show that earnings management positively affects the magnitude of the forecast error, that is, when earnings are manipulated the forecast error appears to be bigger. However, after controlling for a number of control variables such as number of analysts following, size, earnings uncertainty, trade volume and a set of performance variables, this positive impact appears to be driven by accruals earnings management and not by real earnings management. Due to a possible reversed causality between forecast error and earnings management, GMM estimation (Generalised Methods of Moments) is used in order to provide consistent estimators. Moreover, forecasts appear to be more optimistic for companies that manage their earnings downwards through accruals. These findings reveal that analysts may not be as biased as the literature claim, instead, they could be the victims of earnings management.

Chapter 3: Earnings Management and Analysts' forecasts

3.1. Introduction

One of the most important requirements to succeed nowadays is to be money driven. For some, it is the number one factor that drives our ability to be productive, since we live in capitalism. For others, authority could be as important as money or even more important, providing money plus the passion of ruling and leading. Nonetheless, more power means more responsibility and more pressure to deliver. A typical example of this description is what large companies' managers face nowadays.

In the present financial markets, companies' managers are surrounded and monitored by investors, financial analysts, suppliers and even the media from everywhere in the world. Reasonably enough, their priority lies in optimising shareholders' wealth along with their own position and income. To do so, they have to take advantage of every possible tool under their control. Earnings Management is one of the most popular tools in accounting management. Earnings management is the procedure of managing the discretionary variables affecting a company's earnings in order to make it look better, stable, sustainable or high.

There are two major categories of earnings management. accruals-based earnings management and real earnings management. On the one side, Accruals earnings management is the use of estimated discretionary accounts in order to boost or decrease earnings. According to Sloan (1996), earnings consists of two major components: cash flows and accruals. As amounts of cash flows are harder to alter, estimated accruals are more possible to manage in order to change the final figures. From the accruals standpoint, this could be done by recognising sales not yet delivered, changing the inventory methods, timing gains and losses and many more. On the other side, real earnings management is done through adjustment of real operational activities such as accelerating sales in the short term by offering lenient credit terms or surprise discounts; cutting research and development expenses; cutting advertisement expenditures; and overproduction to reach lower unit costs.

There exists a lot of incentives that stand behind earnings management. A lot of todays' companies adopt a compensation plan for their managers which is directly related to the yearly performance. Therefore, financial bonuses and managerial compensations is believed to be a major reason for a manager to adopt earnings management (Bergstresser and Philippon (2006)). In this case, a manager might use his authority to accumulate profits into one particular period using accruals management, which will give allow him to reach his bonus goal. Nowadays, the same incentive could also be exercised differently through options or insider trading. Managers would definitely prefer to trade their stocks during periods of high performance, thus they might seek earnings management to apply their strategy.

Financial markets highly value earnings stability, which is another motive behind earnings management. In this case earnings management is used to smooth out earnings' fluctuations throughout subsequent fiscal periods, in order to build up confidence about the company's performance. For example, managers could decide to defer some of their current profits to cover up for anticipated losses resulting from a bad season. Even though they are able to use some accounting practices to change some figures, they have to be rational in doing so, meaning that they shouldn't be extra aggressive and commit an accounting fraud.

Apart from the incentives that push managers to make use of earnings management, applying such alteration wouldn't pass without any implications. Assuming that these adjustments are done internally and behind the scenes, the most likely affected side would be investors, financial analysts and any market spectator following the underlined company.

The general tendency in the literature observes analysts' forecasts as overall optimistic (DeBondt and Thaler (1990), Easterwood and Nutt (1999) and Larockque (2013), among others) and this applies to different eras and to different financial markets. This finding is also consistent with this research as proved in Chapter 2 of this thesis that employs FTSE all share companies in London stock exchange. Although some of the previous studies raise questions about the rationality of financial analysts, it is still obscure as to what causes these forecasts to look optimistic in a systematic way. Therefore, one cannot simply judge analysts' professionalism by only observing trends in their forecast error. Based on the literature and what was found in the previous chapter, this chapter addresses the reasons why analysts' forecasts look very optimistic and in particular its relationship with earnings management. To our knowledge, Earnings management has never been used as a causality variable to analysts' forecast error. This chapter concentrates precisely on the implication of earnings management and other factors on financial analysts forecast.

Financial analysts are considered a very important source of information that feed the market with daily analysis, reports and investment recommendation. These recommendations are then considered by investors before taking their decisions. Financial analysts' forecasts and recommendations are based on the likelihood of performance of a company, which is estimated using forecasting techniques and fundamental analysis concerning the followed company. There is no doubt that unusual and unexpected alterations using earnings management techniques would make the life of analysts much harder when they attempt to forecast the company's earnings. This will likely lead to a higher forecast error, which is the difference between analyst earnings forecasts and the reported earnings per share. Consequently, this research examines the causal effect of earnings management on forecast error using an empirical approach of earnings forecasts on FTSE all share companies in London Stock exchange between 1993 and 2013.

Preliminary results show that earnings management positively affects the magnitude of the forecast error, that is, when earnings are manipulated the forecast error appears to be bigger. However, this result is independent of the sign of the forecast (optimistic or pessimistic). After controlling for a number of control variables such as number of analysts following, size, earnings uncertainty, trade volume and a set of performance variables, this positive impact appears to be driven by accruals earnings management and not by real earnings management.

According to the literature, one of the main incentives of using earnings management is to boost their companies' earnings and meet public expectations. In doing so, many studies suggest that managers try to meet or beat analysts' earnings forecasts (Burgstahler and Eams (2006), Caramanis and Lennox (2008)). There is a high probability that not meeting these expectations could result in a negative market surprises. Additionally, Roychowdhurry (2006) claims the reason managers choose to manage earnings is simply to avoid showing losses. Conceding that analysts' forecasts are part of the market expectation which is one of the motives behind the use of earnings management, a possible reversed causality could appear between analyst forecasts and earnings management because of the way the forecast error is calculated by taking the difference between the forecast and the reported earnings. The main assumption behind this error is that analysts don't acquire any insider information and therefore concede a genuine error in the end. However, the opposite may not be true. If the earnings were to be manipulated by managers who already know the market expectations of their companies, and push their earnings towards the consensus forecasts before being reported, the overall error might look smaller than without their interference. If this occurs, the Forecast component of the Forecast error will have an impact on the reported earnings per share. Therefore, the analysis will be subject to a reversal causality since the earnings management proxies are assumed to be independent. In order to control for this problem, a precautionary measure is taken by employing System GMM model (Generalised Methods of Moments). The idea behind GMM is that it relies on lagged values being the best available internal instruments of the endogenous factors (in this case abnormal accruals and real earnings management) especially when external proxies are not available. Taking lagged values is very practical in the sense that they are highly representative of level variables, but independent of the level variables of earnings management (since a lagged variable cannot be affected by a future variable).

After breaking down the forecasts into optimistic and pessimistic, results from the GMM regression shows that optimistic forecasts are positively affected by the negative use of earnings management (when earnings are managed downwards). This is due to the unexpected fall of earnings per share making forecasters look optimistic. Moreover, when earnings management is used to boost earnings, reported earnings look higher than usual, surpassing the forecasts and making analysts look pessimistic. Results proved to be robust even after applying a sensitivity analysis that took into consideration possible biased forecasts.

Additionally, findings prove that forecast error is negatively associated with company's performance. For example, forecast error appears to be higher when previous year's performance is negative and when it is uncertain. This is consistent with Gu and Wu (2003) and Ciconne (2005) who suggests that loss firms are harder to predict. Contrary to the literature, number of followers are not found to be significantly related to forecast error[6].

While previous studies have mentioned the role of accruals in various aspects, abnormal accruals and real earnings management have never been used in the literature as

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[6] This was due to a present multicollinearity found between trading volume and number of followers.

determinant factors of analyst forecast error. This study contributes to the literature by examining how earnings management could lead to higher analysts' forecast errors, the same analysts that the literature brands as irrational and extreme. Based on results from the empirical analysis, it is believed that forecasters were unable to anticipate changes in earnings based on accruals management which led to them looking more optimistic. The evidence provided on the relationship between analyst forecast error and earnings management stresses on the importance of following tighter accounting standards and audit control to enforce complete transparency on public companies.

The remainder of this chapter comes as follow. The next section discusses the background and literature review, stating in the end the gaps that are going to be addressed along with the research hypothesis. The third section provides full information regarding the sample selected and the methodology applied. A discussion about the empirical results is provided in section five. The last section concludes.

3.2. Background and Review of the Literature:

3.2.1. Managers' authority and incentives to manage earnings:

The expansion of research in management accounting over the past two decades reflects the extent of reliance managers showed on accountants. When it matters the most, accountants can work their magic out to reshape the books to look in favour of their managers' requests or simply deferring a loss recurring from a poor yearly performance. Despite being committed to the accounting standards, managers do not need a second invitation to try and find a gap from which they can manage their company's earnings. However, one cannot claim that managers commit to earnings management without stating the motives to do so, which are many.

So why and when do managers really need to manage earnings? To start with, financial temptation of bonuses is believed to be a major reason for managers to take advantage of the smallest details in accounting practices to manage earnings. These bonuses depend implicitly and explicitly on earnings reported under their control ((Healy (1985), Bergstresser and Philippon (2006)). Fox (1980) reports that 90% of the largest US companies apply earnings based bonus scheme. Based on this, Healy (1985) examines how companies' accounting procedures change when their bonus plans are modified. The author argues that the manager tracks what is happening to cash flow from operations and non-discretionary accruals throughout the fiscal year, and by the end of each year he would select an appropriate accounting procedure and discretionary accruals to maximize his expected utility from bonus awards. Healy adds that such adjustments help managers to move earnings from one point in time to another, thus accumulating higher amount of profits to one period. Managerial compensation could be exercised using different methods: Bonus plans, performance plans, non-qualified stock options, insurance plans, stock appreciation rights.

Second, another reason of earnings management is believed to be meeting public expectations, more precisely analysts' forecasts. For example, regardless whether a company is making profit or even having a good earnings growth, the fact that it doesn't meet the public expectations will put its managers under pressure and create a negative feeling in the financial market, thus negative impact on the stocks price. This is all due to reputable financial analysts' who release their reports ahead of the actual earnings report date, signalling what could be the performance of the company in the background. Forecasts in return will form a certain atmosphere that will affect the investors' choices regarding a particular company. Therefore, a problem might arise when that company comes up with lower than expected results compared to what investors had in mind (affected by the cloud made out of forecasts). The difference between the reported earnings and forecasts is called either a positive or negative surprise. Consequently, managers will try their best to meet or beat analysts' forecasts and make a positive surprise to boost the stock price. In light of this issue, Burgstahler and Eams (2006) find that managers take accounting and operational actions to increase earnings or lower management forecasts in order to avoid negative earnings surprise.

Third, the stability of reported earnings seems to play a major role in earnings management. DeAngelo et al. (1996) suggest that when a firm breaks the pattern of consistent earnings growth it might face an abnormal drop in stock prices by 14% on average. Consistently, Burgstahler and Dichev (1997) find strong evidence in favour of earnings management. Their result show that a change of small loss to small profit will lead to big gain in marginal benefits, with 33% to 40% of firms decrease exercise discretion to avoid reporting losses. Their test is based on two assumptions. The first is that managers prefer not to report a decrease in earnings to avoid the costs imposed on the firm in transactions with stockholders. The second is the prospect theory which implies that the fear of reporting in red ink will push managers to manipulate earnings.

Fourth, the accounting side of earnings management could also be used to send some hidden messages to investors regarding the economic performance of the company, such as understating earnings in order to give the company a bigger probability to grow financially in the future. If so, earnings management would be considered in favour of shareholders rather than an attempt to hide the company's true performance. A, alternative description of earnings management was made by Ayra, Glover and Sunder (2003) who call the relationship between earnings management and financial statements as a casting photography between a model and a photographer. As the model poses and smiles to the camera, the photographer takes pictures while changing the camera angle and settings in reaction to the model. The same would be applicable to businesses where managers manage accruals to come up with better financial figures.

Fifth, many studies have showed that managers overstate earnings during the year surrounding an IPO (Teoh, Welch and Wong (1998), Teoh, Wong and Rao (1998), Rangan (1998) and Shivakumar (2000)). Teoh, Wong and Rao (1998) for example use Depreciation and Bad debt provisions to detect earnings management. They report that IPOs provide managers with many opportunities to take advantage of, mainly through earnings management. According to Teoh et al (1998), managers could manage their IPOs earnings upwards to attract more trade and boost the stock price. After analysing 1682 firms IPO going public between 1980 and 1990, they find that IPO firms use more income-increasing depreciation methods and provide less for uncollectible accounts receivable. Their findings are consistent with studies using abnormal accruals as a proxy for earnings management.

On November 22nd 2001, "The Economist" reports that many of Standard and Poor's listed companies artificially boost their profits. They add: "operating profits for the S&P 500 have been inflated by at least 10% a year over the past two decades, thanks to a mix of one-time write-offs and other accounting tricks. Such sleights of hand mean that American shares may be even dearer than they look". One of S&P 500 best performers was General Electric with $10.7 billion in earnings in 2000 FY. It occupied the index's biggest capitalisation after 100 consecutive increases in quarterly reported earnings until 2001. At that particular point, no one could deny the fact that General electric had such business diversity and market domination that led to such earnings growth. However, breaking the record of increase in quarterly earnings needed more than just true reflection of business activities. It simply needed the magic of earnings management which is done by perfectly timing gains and losses to smooth out any fluctuation and avoid a fall.

But how could managers pre-manage earnings? And to what extent are they able to do so? Two ways of earnings management could be employed: Accounting earnings management (Accruals-Based) or Operating activities (Real Earnings Management). While operating activities are hard to be captured as it depends specifically on the type of business and industry each company operates in, the literature focused more on accounting decisions that could be used by managers in order to manage earnings. Nevertheless, real earnings management has emerged in the last decade as a hot topic in accounting and finance fields.

3.2.2. Accruals-based earnings management:

It is by no accident that accruals management is a main factor in determining current earnings. Sloan (1996) finds evidence that current earnings persists into the company's future performance, and this depends mainly on the cash flows and accrual components. Thus instead of relying on statistically motivated models in order to predict future earnings, Sloan (1996) proposed a new model using characteristics of the accounting process documented in the financial statement analysis, including accruals and cash flow as components of current earnings. According to Ayra et al. (2003), although accruals and cash flows are both components of the current earnings, however, they have different implications on future earnings. For example, if high future earnings are derived mainly from accruals, they are less likely to persist than if they were derived mainly from cash flows. Using 30 years of financial data for NYSE and AMEX firms, the authors state the following hypothesis: "The persistence of current earnings performance is decreasing in the magnitude of accrual component of earnings and increasing in the magnitude of the cash flow component of earnings" Sloan (1996, page 291).

Richardson, Sloan, Soliman and Tuna (2005) extend the work of Sloan (1996) by focusing on the reliability of earnings persistence and report that less reliable accruals result in lower earnings persistence. They also point out that investors do not anticipate the reliability of accruals in their valuation of stocks, which leads to significant security mispricing. Fairfield, Whisenant and yohn (2003) find that future profitability and firm value depend on growth in net operating assets as well as current profitability. Therefore, they argue that Sloan (1996) had overlooked the role of accruals as a component of growth in net operating assets. Consistently, as accruals and cash flows were considered components of current earnings, growth in net operating assets could also be disaggregated in two components: Accruals and growth in long-term net operating assets. After using Return on Assets (ROA) as a performance measure instead of net income variable, they prove that one-year-ahead ROA is negatively associated with both components: accruals and growth in long term net operating assets. Moreover, they find no difference in persistence between the two components contrary to what Sloan (1996) had proved. Regarding this, Fairfield et al. (2003) then record the following: "the lower persistence of accruals relative to cash flows from operations is more likely to result from the conservative bias in accounting principles or the lower rate of economic profits that result from diminishing marginal returns to new investment opportunities, or both. At the same time, the lower persistence of accruals is less likely to result from other features of accruals, such as their susceptibility to manipulation by management."

According to Degeorge, Patel and Zeckhouser (1999), within generally accepted accounting principles (GAAP), managers have significant power in deciding the way some accounts are managed. Whenever possible, they could interfere in the following:

- Choosing inventory methods (LIFO, FIFO, weighted average inventory cost…)
- Allowance for bad debt
- Expenses for Research and Development, Advertisement or maintenance.
- Recognition of sales not yet delivered
- Estimation of pension liabilities
- Capitalisation of leases and market expenses
- Delay in maintenance expenditures

One of the managers' most effective ways to manage earnings is deferring expenses or boosting revenues which could be done by lowering prices or timing gains and losses. For example, they could lend some of the big income of today to the future in case they expect a big disappointment in the near future. Even though they are able to use some accounting practices to change some figures, they have to be rational in doing so, meaning that they shouldn't be extra aggressive and commit an accounting fraud.

Despite not being officially standardised or agreed on, earnings management is widely used and well known among most practitioners and academics who, in fact, describe it using different terminologies: “Income smoothing, Accounting hocus-pocus, Financial statement management, The numbers game, Aggressive accounting, Reengineering the income statement, Juggling the books, Creative accounting, Financial statement manipulation, Accounting magic, Borrowing income from the future, Banking income for the future, Financial shenanigans, Window dressing, Accounting alchemy…”

Bergstresser and Philippon (2006) also discuss few reasons as to why managers could manage earnings. They denote that: “The opportunity to manage earnings arises in part because reported income includes cash flows as well as changes in firm value that are not reflected in current cash flows. While cash flows are relatively easy to measure, computing the change in firm value that is not reflected in current cash flows often involves a great deal of discretion. The accruals’ components of income capture the wedge between firms’ cash flows and reported income” (Bergstresser and Philippon (2006) p. 4).

In order to estimate earnings management, Jones (1991) concentrates on how to estimate the abnormal accruals arising from managers’ accounting tricks in earnings management. Jones (1991) was able in this way to deduct abnormal accruals from total realised accruals, after defining what could be total normal accruals, Consistently, abnormal accruals will also be equal the difference between discretionary and non-discretionary accruals. Abnormal or manipulated accruals is also called unexpected accruals. The literature heavily relates unexpected accruals to earnings management due to the fine evidence found between management incentives and the use of accruals.

In a working paper based on the cross sectional model of Jones (1991), Chen and Cheng (2002) investigate the causal relationship between abnormal accruals and abnormal stock returns. After decomposing abnormal accruals to opportunistic earnings management incentives and other incentives, they find that future abnormal returns are positively associated with abnormal accruals reported for performance. Similarly, Rangan (1998) investigate 712 IPO cases and report that stock market overvalues earnings of the related firms during the issuing year, then stock prices drop short after the announcement. Rangan (1998) conclude that issuing companies can stimulate their stock prices through earnings management. He backed his idea by arguing that: “the market appears to extrapolate earnings growth associated with discretionary accruals and hence overvalues issuing firms. Subsequent to the offerings, when the reversal of discretionary accruals causes earnings to decline, the market is surprised and corrects its valuation errors”.

Despite agreeing that accruals and net income are abnormally high prior to an IPO announcement, Shivakumar (2000) had an alternative explanation of the share price reaction following to the IPO year. Shivakumar (2000) argues that investors appear to take into account earnings management prior to offering announcement, hence share price drops at the announcement as a result of correcting overstated earnings using earnings management and not because of the reversal of accruals management as Rangan (1998) had stated.

Xie (2001) also examines the reaction of the financial market to abnormal accruals using Jones (1991) model. After analysing data of 7506 firms for a sample period from 1971 until 1992, Xie (2001) find that markets severely overpriced abnormal accruals during the investigated sample. Moreover, results show that this overpricing is not exclusive to IPOs or seasoned equity offerings as stated by Rangan (1998) and Teoh et al. (1998). Consistently, Chi and Gupta (2009) provide evidence that stock overvaluation leads to higher discretionary accruals, but the latter is associated with negative abnormal future stock returns.

The incentives and consequences of abnormal accruals are discussed by Iatridis and Kadorinis (2009), who investigate 239 companies listed in London Stock Exchange in the year of 2007. Based on Jones (1991) model, Iatridis and Kadorinis (2009) show the following:

- Companies that choose to voluntarily disclose accounting figures tend to use less earnings management. A negative correlation between voluntarily accounting disclosures and operating cash flows "would be indicative of earnings management as firms would be inclined to increase accruals when operating cash flows are low" (Iatridis (2009, p. 169)).
- Firms seeking to meet or exceed financial analysts' forecast are more likely to use earnings management that is by displaying higher discretionary accruals.
- Firms that issue debt and equity capital are more likely to have abnormal accruals.
- The use of earnings management boosts manager's compensation.

In a similar manner, Bergstresser and Philippon (2006) assess the relationship between earnings management and the value of CEO stocks and option holdings, known as insider ownership. Their result suggests that CEO's whose wealth is more sensitive to the firm's share price, lead their companies to higher earnings management. Moreover, "periods of high accruals coincide with unusually significant option exercises by CEOs and unloading of shares by CEOs and other top executives". Recently, Kraft, Lee and Lopatta (2014) investigate senior officers' incentives in meeting managerial forecasts through earnings management, particularly accrual based earnings management before selling or buying their own shares. Similar to Bergstresser and Philippon (2006), Kraft et al. (2014) stress on the importance of insider ownership and private information and claim that managers stimulate earnings in order to meet voluntarily disclosed earnings estimates. Based on EPS management forecasts collected from First Call's Company Issued Guidance (CIG) database for the period 1996–2010, Kraft et. Al. (2014) examine the following two areas: The first is whether insiders trade their shares (mainly sell side) depending on their anticipation of future returns; The second is the role of accrual based earnings management in making reported earnings meet management earnings estimates. They discover that insiders sell shares in anticipation of future lower returns. Moreover, their results "indicate that only insiders who have the ability to affect financial reporting through earnings management can influence the probability of meeting management earnings forecasts before they sell stocks"(Kraft et al. (2014) p.120)).

Another interesting point brought to light by Caramanis and Lennox (2008) as they link audit effort to earnings management for Greek companies between 1994 and 2002. While auditing hours is used as a proxy of audit efforts, abnormal accruals model based on Jones (1991) is used to estimate earnings management. They find that when there is less audit efforts, earnings management appear to be used intensively and vice versa. Moreover, the authors state that it is highly probable that companies manage earnings upwards to avoid falling in negative earnings.

3.2.3. Real earnings management:

Research surrounding real activities earnings management has been growing simultaneously as key component of earnings but the estimation of such activities appears to be hard. Academics and professionals referred to real earnings management as real adjustments made to operational activities in order to affect the final earnings figure. Roychowdhury (2006) defines "real activities manipulation as departures from normal operational practices, motivated by managers' desire to mislead at least some stakeholders into believing certain financial reporting goals have been met in the normal course of operations. These departures do not necessarily contribute to firm value even though they enable managers to meet reporting goals".

As a matter of fact, real earnings management is considered earnings manipulation when extensive adjustments on real activities are made putting the company's value under risk on the long run. Even though managers implicitly know about the cost of such adjustments, they prefer to carry on rather than relying solely on accruals management of earnings since accounting decisions are highly supervised by auditors and regulatory scrutiny. This preference is studied by Graham, Harvey and Rajgopal (2005) who state that managers prefer to use operational activities to smooth earnings rather than accounting manipulation, even though short operational decisions might have a negative long term impact on the performance of the company. After surveying and interviewing more than 400 executives, Graham et al. (2005) find that managers opt to delay maintenance and advertising expenses or even give up a positive long term investment in order to meet the short term earnings expectations as they fear a negative stock market reaction. The authors back their argument by saying: "This tendency to substitute real economic actions in place of accounting discretion might be a consequence of the stigma attached to accounting fraud in the post-Enron and post-Sarbanes–Oxley world". Similarly, Bushee (1998) investigates whether companies owned by institutions tend to reduce research and Development in order to boost earnings. On the one hand, their results show that only firms with extremely high institutional ownership could decrease R&D costs to boost earnings. On the other hand, a normal proportion of institutional ownership might help monitoring managers to maintain a long term positive performance, therefore managers don't reduce R&D expenses in favour of a short term result.

In order to detect real earnings management, Roychowdhury (2006) believes that managers aim to avoid losses in order to manipulate earnings. Therefore, the author attempts to investigate abnormal levels of Cash flow from operations, discretionary expenses (sum of R&D, advertisement, selling, general and admin expenses) and production costs for firms close to the zero earnings benchmark. Roychowdhury suggests that these patterns will be caught if there was acceleration in timing of sales, increase in price discounts, reduction of discretionary expenditures, increase in production and low COGS reports. A sample of 4252 companies led to prove the following:

- Abnormal CFO and abnormal discretionary expenses are unusually low for zero earnings firms (5.91% lower than normal firms).

- Abnormal production costs of zero earnings firms are unusually larger by 4.97% than the rest of the sample.
- Consistent with overproduction, suspect firms are found to have high inventory growth compared to other firms.

On the 30th of July 2002, the Sarbanes-Oxley (SOX) act came to light in the US to ensure more accurate and transparent financial reports submitted by public companies in NYSE. One of the main act's requirements (section 404) requires from companies to "state the responsibility of management for establishing and maintaining an adequate internal control structure and procedures for financial reporting and contain an assessment, as of the end of the recent fiscal year of the issuer, of the effectiveness of the internal control structure and procedures of the issuer for financial reporting" (Sarbanes-Oxley Act 2002, US public Law 107-204). It also requires that companies must report how these internal controls were made by the board according to the standards set. Accordingly, Cohen, Dey and Lys (2008) examine the evolution of earnings management before and after the SOX act 2002. Cohen et al (2008) assume that such SOX act may have had a significant impact on companies' employment of earnings management specially the accounting side of it. After analysing 8,157 US listed companies, their results how that while accrual-based earnings management were high prior to SOX act, they decreased significantly after 2002. They also find that the intensive use of accruals management was consistent with insiders' equity-based compensations. However, managers seem to have relied more on real earnings management instead of accrual-based ones after the implementation of SOX.

Cohen and Zarowin (2010) study the use of accrual-based and real earnings management around seasoned equity offerings (SEO). In a study based on completed US offers from NYSE, NASDAQ and AMEX, their finding shows that the use real operational manipulations is the main reason behind the decline in post-SEO operating performance. Zang (2012) also delve into the trade-off between real and accrual-based earnings management. Zang argues that managers' decision regarding this trade-off is based on the relative cost of each of the two. For example, managers would rely on accruals management when their company is not competitive enough in the industry, being in an unhealthy financial position or having high current tax expenses. According to the same author, managers adjust their accruals levels according to real earnings manipulation realised. Nevertheless, with higher level of monitoring and limited accounting flexibility, managers intend to use real earnings management.

Gunny (2010) claim that accruals-earnings management is costlier and less flexible to use thus managers might prefer real earnings management instead. This is because an excessive use of accruals management might face the risk of SEC scrutiny (Security and Exchange commission) and class action litigation. Moreover, accruals management is done after the fiscal year-end leaving managers in less flexible position and facing the restriction over which accounting treatments would be allowed by auditors at that time. Therefore, Gunny (2010) studies the relationship between real earnings management and future performance in the US from 1987 and 2003 by focusing on a sample in which earnings management incentives are high (excluding utility and financial industries). Results show that Real earnings management is positively associated with companies who just meet their earnings benchmark (maintained last years' earnings) compared to firms who do not use earnings management and miss the benchmark by more than 1%.

3.2.4. Earnings forecast error:

An extensive body of the literature investigates the information content of earnings forecasts and stock recommendation. A lot of these studies find evidence of inefficiency of stock markets after they discovered unusual stock returns following the release of analysts' results. One of the reasons behind this inefficiency was attributed to financial analysts that appear to overestimate earnings and stimulate the market. This gap pushed towards more research studying forecast accuracy. For example, De Bondt and Thaler (1990) try to find an explanation why analysts forecasts are mostly optimistic and too extreme in NYSE companies between 1976 and 1984. In their analysis, they focus on two major market variables in the in order to explain why forecast errors were large: Market value to book value of equity (MV/BV), and earnings growth. However, none of the variables explains much of the forecast error. They conclude that behavioural bias is behind this error since analysts are decidedly human, and their results could be biased in some way or another.

Das, Levine and Sivaramaknishnan (1998) find a strong relationship between earnings unpredictability and analysts' forecast accuracy. In an empirical study using time series data from 1969 to 1987, the authors construct a score of unpredictability using past forecast error, then they apply this score to the main regression analysis formed on 239 firms for a period between 1989 and 1993. They also include the number of analysts following a company and the size of the company as they might have an effect on forecast error. The authors find no relationship between analysts forecast error, number of followers and size. However, they state that forecast error was larger for companies with higher unpredictability scores. Similarly, Lim (2001) uses the variability of earnings over 8 previous quarters in an attempt to explain the forecast error in the US. Despite having a significant positive relationship between earnings variability and forecast error, it isn't as strong as the author expected. Beckers, Steliarcs and Thomson (2004) also study the relationship of uncertainty around companies' earnings by adding the dispersion of analysts' forecasts as a proxy of earnings unpredictability. Their results show that forecast optimism increases with higher analysts forecast dispersion and with higher stock returns volatility.

In regards to how analysts perceive earnings news, Easterwood and Nutt (1999) identify three hypotheses regarding the reaction of an analyst: Analysts systematically underreact to earnings news; analysts systematically overreact to earnings news; and analysts are generally optimistic to new information. According to the researchers, identifying these hypotheses is very important "(…) because it might indicate whether analysts irrationally err in processing earnings-relevant information or whether their forecast errors are more consistent with their economic incentives". While the first and the second hypotheses are independent of the type of information, they find statistical evidence that analysts underreact to negative information and overreact to positive information, with an overall optimistic interpretation of information. Easterwood and Nutt (1999) also find that after revising prior year forecasts, analysts tend to underreact to abnormally negative news and overreact to abnormally positive ones. Gu and Wu (2003) find evidence that "part of the observed analyst forecast bias could be a result of analysts' efforts to improve forecast accuracy when the earnings distribution is skewed". After regressing Skewness over the forecast bias, results show a significant relationship between earnings Skewness and earnings forecast bias at 1% confidence level.

Ciconne (2005) suggests that previous year's profit and loss might play a major role in the accuracy of forecasters. The author uses size, Book-to-Market ratio and Loss dummy dummy variables as explanatory variables of forecast errors. Results show that loss firms are more difficult to predict. Moreover, forecast error is bigger for firms that saw losses than the ones that achieved profit. However, forecast errors are decreasing over time and analysts are not as optimistic as the literature states. In addition, Ciconne suggests that it is hard to believe that analysts release favourable forecasts in order to access private information, as in this case they are very likely to sacrifice their reputation of submitting unreliable reports (in accordance with managers' preferences), which will slowly harm their reputation. The risk of future failure in this case is higher than the return from accessing private information according to the author.

Lately, Baron, Biard and Liang (2013) focus on the timing of release of analyst forecast and its impact on trading volume. They find that pessimistic forecasts are issued later than other forecasts on average, which may explain why the last quarter of a fiscal year is less optimistic in terms of earnings forecast.

3.2.5. Relationship between managers and analyst forecasts:

According to the literature, bias in earnings forecasts is not always genuine as it could be driven by the fact that analysts might shift their analysis to suit managers' preferences in return of private information. Mest and Plummer (2003) for example suggest that companies' managers play an important role in the biases of analysts forecast since optimistic forecasts can improve the chance for an analyst to access the management. Therefore, if management give less attention to the forecasted measures, analysts will turn to be more rational and accurate. Accordingly, they test this prediction by examining sales and earnings forecast and find that analysts' forecasts are too high. This theory is consistent with findings of Das, Levine and Sivaramaknishnan (1998) who denote that those publishing low earnings forecasts have more access to management's insider information thus analysts will demand private information for hardly predictable firms by issuing less aggressive forecasts.

Lately, the relationship between managers and analysts and its impact on analysts' forecasts have been covered in many studies (Ke and yu (2006), Libby et. Al (2007), Bernhardt and Campello (2007)). Libby, Hunton, Tan and Seybert (2007) state that not only analysts have an advantage in having good relationship with managers, managers may indirectly push analysts to release good reports regarding their company, as a trade off with accessing private information. Bernhardt and Campello (2007) note that firms might, on purpose, generate earnings that exceed the analyst forecast, in order to make a positive surprise and stimulate the stock prices, and this could be done via various accounting methods. However, one could also think that a company might somehow convince analysts to issue lower earnings forecasts thus the earnings surprise will turn to be positive. Therefore, Bernard and Cambello focus on Quarterly data from Institutional Brokers Estimate System (IBES), gathering data prior to the US Regulation Fair Disclosure from 1989 to 1999. They find that forecasts released late in the year have more impact on the investment decisions. Beside, firms for which the forecasts fall just before the announcement date earn far higher returns around the announcement period than those which have high earnings expectations, marking an impressive difference of 69%.

A more direct approach was applied by Richardson, Teoh and Wysocki (2004) who investigate the relationship between managers and analysts' forecasts via managerial incentives to sell stocks after earnings announcement. The authors main interest was to justify why analysts systematically revise their earnings forecasts downwards until just before the announcement day. According to their theory, managers use new equity issues in an attempt to sell stocks on behalf of the company or from their personal accounts using options. Therefore, as the time approaches the announcement date, managers use their relations with analysts to walk down their earnings forecasts to achieve a positive surprise in the end by beating the earnings targets. Richardson et al. (2004) use a sample of analyst forecasts from 1980s to 2001 from IBES database and insiders' trades from open-market purchases and sales and option excercises from Thomson Financial's compilation. Consistent with their hypothesis, they find that analysts forecast tend to be pessimistic just before the announcement day. More interestingly, this finding is "more common for companies that are about to issue new equity and whose insiders are net sellers of the firm's stock in the quarter immediately following an earnings announcement" (Richardson et al. (2004, p.890)).

3.3. Hypothesis Development and Research contribution:

Based on the above documentation, managers are well documented to be managing earnings using abnormal accruals and real activities management due to many incentives. Applying such manipulation is managed internally, leaving no possibility for information leakage. As a result, there is no doubt that this unusual alteration would make the life of analysts much harder when they attempt to forecast the company's earnings. As a matter of fact, forecasters will become less accurate when earnings management is present, and this difficulty should be reflected in higher forecast error in general. While many studies have mentioned the role of accruals in various aspects, abnormal accruals and real earnings management have never been used in the literature as an explanatory factors of analyst forecast error. This study contributes to the literature by examining how earnings management could lead to higher analysts' forecast errors, the same analysts that many studies brand as irrational and extreme.

Notwithstanding, many would argue that managers do manage earnings in order to meet or beat the forecasts. In fact, this reason is comprehensively discussed in the literature as a major motive behind earnings management, and surely the existence of this theory should lead to lower forecast error. Consequently, this study takes into account this possibility and controls for it by separating optimistic forecasts from pessimistic ones. The main argument behind this separation is that when managers try to meet or beat the forecast, the forecast error will eventually be either zero or negative, since the reported earnings are equal or slightly higher than the forecast. Under these circumstances, optimistic forecasts cannot be a result of managers trying to meet or beat analysts' forecasts. Besides, earnings management is not only used to "meet or beat" earnings forecast, it could also be used to push for higher managerial compensations; for insider ownership and insider trading purposes; disclosing less information about the company's performance; boosting returns on stocks surrounding an issuance and many more.

As a starting point, the first hypothesis attempts to provide a broad picture of the relationship between forecast error and earnings management which comes as follow:

Hypothesis 3.1: The use of earnings management will increase the earnings forecast error made by analysts.

This first scenario is achieved by taking the absolute value of earnings management and the absolute value of forecast error. The reason of taking absolute values is to check how in general the use of earnings management, regardless positive or negative, could affect forecast error. A positive significant coefficient is expected to be seen from this relationship.

However, the story wouldn't have been completed by only taking the absolute values since a lot of behavioural aspects are involved in this association and if hidden, could misrepresent the true association under investigation. One of these aspects is the forecast optimism which occurs when the average forecast falls above the reported earnings per share. Again, the separation of optimistic and pessimistic forecasts is crucial to control for accurate forecasts being a result of managers trying to meet or beat these forecasts. Consequently, the second hypothesis could be seen from the following:

Hypothesis 3.2: Managing the earnings downwards will increase the optimism of earnings' forecasts.

As stated in the literature, there are many reasons to believe that earnings could also be managed downwards. Several incentives stand behind negative earnings management such as to "smooth earnings over a set of periods", "banking profit for the future" or "taking a Big Bath" and many more. Earnings smoothing is done to strengthen the stability and earnings sustainability in firms. Banking profit for the future is to simply delay the announcement of a certain profit in order to accumulate larger amount for the future, which might lead to higher bonus rates for managers or simply to cover up anticipated bad periods. Taking a big bath is well known by practitioners when managers decide to take all the negatives in one go rather than splitting the negative earnings over many periods. From all the previous examples, the second hypothesis suggests that forecast error increases when earnings are managed downwards since the consensus forecast remains unchanged while earnings are being altered.

Hypothesis 3.3: managing the earnings upwards should significantly lead to negative forecast errors (showing more pessimistic forecasts).

The objective of the third hypothesis is to prove what was suggested in hypothesis 3.2. As earnings increase due to earnings management, the probability of having pessimistic forecasts will increase since forecasts are more likely to fall below the reported earnings per share. Therefore, the coefficient from testing hypothesis 3.3 is expected to be significantly statistically positive.

Coming back to the main assumptions set at the beginning of this section, a problem would arise if for any reason insider information was leaked. A valid example in the literature is when managers try to put some influence on analysts in order to lower their earnings forecast by revising their forecasts downwards before the earnings announcement day, allowing managers in return to avoid negative surprises. Hypothesis 3.4 takes into account these biased forecasts:

Hypothesis 3.4: After excluding biased forecasts, the use of positive earnings management will increase analyst forecast error.

The biased sample consists of those companies for which forecasts are systematically revised downwards by more than 20% in the last 6 months before the earnings announcement date. Since the excluded biased forecasts tend to become more accurate than the rest of the forecasts due to the nature of information leakage, using the net sample is expected to generate a higher impact of positive earnings management on forecast error.
The main objective of drawing such a hypothesis comes at the back of a big debate regarding the use of earnings manipulation and its consequences on the stock market. This study will try to contribute to the literature by pointing out at another negative consequence of earnings manipulation which is the extremism of analyst forecasts. While many attribute extreme figures of forecast errors to the irrationality of earnings forecasts, in fact, earnings manipulation could be a main driver behind these extreme figures. By using quantitative analysis and Generalised Methods of Moments to control for possible endogeneity, results of such research and relative studies should push towards more transparency and rationality in the financial markets.

3.4. Sample selection

In order to observe the reasons behind earnings forecast error in the UK, all companies in London stock exchange are used as available every year from 1993 to 2013. It is important to start the sample from year 1993 which is one year after the introduction of the third financial reporting standard (FRS3) in the UK. Therefore, to ensure that all companies have adopted the FRS3 into their reports, January 1993 is considered as the starting point. Regarding the information content of this new standard, Acker, Horton and Tonks (2002) explains that “UK companies are now required to provide more details in the income statement, distinguishing between continuing, discontinued and acquired operations. The income statement must also identify gains and losses on the sale of termination of an operation, the costs of fundamental organisation or restructuring, and gains and losses on the disposal of fixed assets. Furthermore, the Earnings per share must now be calculated after taking account of all unusual items, extraordinary and exceptional, whereas under SSAP3[7] extraordinary items were omitted from EPS”. (Acker, Horton and Tonks (2002, p. 196)).

[7] SSAP 3 represents “Earnings Per share” in Acker et al. (2002).

Actual earnings per share (EPS), forecasted earnings per share and number of analyst forecasts are collected from IBES database (Institutional Brokers Estimate System) available on Datastream Thomson Reuters. Worldscope database is used to collect the rest of historical data. Yearly averages of monthly forecasts are calculated in order to calculate yearly forecast errors. Since analysts publishing their forecasts later in the financial year have more information in hand than others who published earlier, it is not fair to treat all months on a same basis. Therefore, weighted averages of monthly forecasts are also used depending on the time of forecast but results of both variables (weighted and normal averages) were very similar.

Companies listed in FTSE all Share are collected individually, reflecting the true number of companies listed in each year of the sample period separately. This is essential since the number of listed companies will vary from year to year due to mergers, acquisitions, new entrants or companies leaving the index. Table 3.1 below shows the distribution of public companies in FTSE all share index and the ones which are available for this study throughout 20 years from 1993 till 2013. With an average of 746 firms per year, the highest number of companies listed in FTSE all share was in 1995 with 903 companies, whereas the lowest was in 2013 with 603 listed companies. The highest number of companies available for this study was for 1997 (727 companies) and the lowest was in 2013 with 438 available companies. Having all companies from the index in the analysis is essential to capture the overall variation of forecast error in London stock exchange. By doing this, the index itself is being under investigation regardless of the individual constituents' characteristics. Moreover, survivorship effect of big companies is being avoided. The sample included an impressive total sum of 1,099,741 analyst forecasts which followed 12,367 firms over 20 years. It's known that analysts keep on forecasting earnings until the earnings actual release date and not when companies close their accounts. Consequently, monthly earnings' forecasts are studied in this research up until results are announced each year. In other words, earnings per share forecasts targeting the next fiscal year end are observed monthly from 11 to 1 month prior to earnings announcement date. The first month is eliminated precautionary since it might contain mixed data belonging to current and previous year if fiscal year end date falls in the middle of the month. Besides, companies followed by less than 3 forecasters were eliminated due to reliability issues and to be consistent with the literature.

Table 3.1 Distribution of total number of firms listed in FTSE all share index, available firms for this study and analysts' forecasts in years.

year	Total number of firms listed	Available Firms	available analyst forecasts
1993	806	625	57751
1994	862	667	60649
1995	903	711	60408
1996	902	718	61624
1997	896	727	62878
1998	896	726	62413
1999	840	686	64349
2000	814	656	53555
2001	772	614	32635
2002	726	588	35958
2003	702	573	37133
2004	702	574	42636
2005	706	580	46279
2006	685	551	42905
2007	694	545	46458
2008	674	524	49239
2009	616	468	50324
2010	623	470	54644
2011	627	470	60169
2012	622	456	60226
2013	603	438	57508
average	**746**	**589**	**52,369**
total	**15,671**	**12,367**	**1,099,741**

3.5. Research Design

For each firm month, analyst forecast error is defined as the difference between the monthly forecast and the yearly reported earnings per share, deflated by the reported earnings per share. This combination will produce a percentage of error made by forecasters when forecasting earnings per share.

a. $$\boldsymbol{FE_{hT} = \frac{F_{ht} - E_t}{|E_t|}}$$

b. $$\boldsymbol{FE_T = \frac{\sum_1^{11} FE_{ht}}{11}}$$

Where FE is forecast error made in month h for year t , F_{ht} is the EPS forecast in monthly horizon h for year ending t, Et is the actual EPS at year ending t. “h” is the monthly distance (11 to 1 horizon) from which the forecast was made until earnings announcement date. Equation *b* then shows how average yearly forecast error was calculated using 11 monthly forecast errors.

c. $$\boldsymbol{|FE_{ht}| = \left|\frac{F_{ht} - E_t}{E_t}\right|}$$

d. $$\boldsymbol{|FE_T| = \frac{\sum_1^{11} |FE_{ht}|}{11}}$$

The absolute value of FE in equation *c* focuses solely on a how far the forecast was from the reported EPS regardless the sign of the substitution. The interpretation of the relationship between this ratio and the rest of the variables will be straight forward regardless of the nature of the forecasts (Optimistic or pessimistic).

Other studies tend to use the stock price as a denominator (Ali, Klein and Rosenfeld (1992)). However, So (2013) states that “because to the extent that equity prices reflect earnings expectations created by analyst forecasts, the numerator and denominator of forecast error could move in tandem, which can potentially induce spurious cross-sectional variation (Ball, 2011; Cheong and Thomas,2011)”. Consequently, using price as a denominator was avoided in this study. Moreover, Observations for which earnings per share is less than 5 pence were excluded because FE cannot be defined when EPS is 0, and small values of EPS can result in extreme values in FE thus influencing the result.

Since forecasted earnings are sensitively affected by any new information, private or public, it is normal to deduce that analysts conducting a forecast at the end of the year have an advantage over the ones doing it at the beginning of the year since they have more information in hand. Therefore, it was unfair to treat all monthly forecasts equally.

Instead of calculating the normal arithmetic average, weighted average of monthly earnings forecast is used depending on the distance of each month to the end of the fiscal year. Hence, a weight of 1 will be given to the first month of the year and 12 to the last month just before earnings are announced. Weighted averages as well as normal averages are used in regressions where yearly averages are used.

3.5.1. Detecting Accruals based earnings management:

Employed by Bergstresser and Philippon (2006), Caramanis and Lennox (2008) and Iatridis and Kadorinis (2009),Jones (1991) consider the following component as the non-discretionary accruals:

e. $NDA_t = \beta_1 \left(\frac{1}{Asset_{i\,t-1}}\right) + \beta_2 \Delta Rev_{it} + \beta_3 PPE_{it}$

f. $TAC_{it} = \beta_1 \left(\frac{1}{Asset_{i\,t-1}}\right) + \beta_2 \Delta Rev_{it} + \beta_3 PPE_{it} + \varepsilon_{it}$

Where NDA_t is non-discretionary accruals, TAC_{it} is the total normal accruals for firm i at time t, β is the slope coefficient for i ε {1,2,3}; $Asset_{i\,t-1}$ is the lagged assets of firm i at time t-1; ΔRev_{it} is the change in revenue for firm i at time t, scaled by the lagged value of assets; PPE_{it} is the plant, property and equipment for firm i at time t scaled by the lagged value of assets; ε_{it} is the stochastic error term. Consequently, any deviation from NDA is used as a proxy estimation of abnormal accruals. In this case it will be measured byε_{it}.

g. $TAC_{it} = \frac{\Delta CurA_{it}}{Asset_{i\,t-1}} - \frac{\Delta CurL_{it}}{Asset_{i\,t-1}} - \frac{\Delta Cash_{it}}{Asset_{i\,t-1}} + \frac{\Delta Sdebt_{it}}{Asset_{i\,t-1}} - \frac{Dep_{it}}{Asset_{i\,t-1}}$

Where TAC_{it} is total accruals for firm i at time t; $\Delta CurA_{it}$ is change in current assets for firm i at time t; $\Delta CurL_{it}$ is the change in current liabilities of firm i at time t; $\Delta Cash_{it}$ is the change in cash holdings and short-term investments for firm i at time t; $\Delta Sdebt_{it}$ is the change in short-term debt and current portion of long-term debt for firm i at time t; Dep_{it} is the depreciation and amortisation expense for firm i at time t; and $Asset_{i\,t-1}$ is the lagged assets of firm i at time t-1.

However, Dechow, Sloan and Sweeney (1995) suggest that Jones model is subject to earnings management miss-specification by assuming that revenues are nondiscretionary since it ignores the fact that earnings could be managed through discretionary revenues. Consequently, a modified version of Jones model was proposed by Dechow et al. (1995) to account for this issue by taking away the change in receivables from the change in revenues.

h. $TAC_{it} = \beta_1 \left(\frac{1}{Asset_{i\,t-1}}\right) + \beta_2(\Delta Rev_{it} - \Delta Rec_{it}) + \beta_3 PPE_{it} + \varepsilon_{it}$

All else being as described above, ΔRec_{it} is the change in receivables from year t-1 to year t for firm i.

3.5.2. Detecting Real earnings management:

As described by Roychowdhury (2006), most of the evidence in the literature on real earnings management discusses the adjustment of Research and Development expenditure to boost earnings per share as a short term solution. Nevertheless, real earnings management doesn’t solely rely on R&D expenditure and it can take many forms. Cutting advertising costs or providing time discounts to increase sales towards the end of the year are examples of other ways to manage earnings.

Three main measures are adopted in this research to estimate real earnings management following Roychowdhurry (2006). However, it is important to discuss the main methods of real earnings management before showing the calculations:

- Sales acceleration: in order to boost sales on a short term, managers might tend to offer limited time price discounts or more lenient credit terms. Both methods are used to stimulate customers in order to boost sales. Despite total earnings in the current period are expected to be higher, cash inflows are likely to drop due to price discounts and credit sales.
- Cutting discretionary expenditures: discretionary expenditures here are mainly R&D expenditures, advertising expenditures and SG&A expenses (Selling, General and Administrative expenses). A surprise cut in these expenses will lead to an increase in current earnings. Roychowdhurry (2006) considers SG&A as it includes sometimes employee training, maintenance and travel expenses which are mostly estimated costs.

- Overproduction: in order to manage earnings upwards, managers can decide to decrease marginal costs by producing more units than necessary. As production increases, average fixed cost decreases. Consequently, as long as the reduction in fixed cost is not offset by an increase in variable costs, cost of goods sold will eventually be lower than the normal cases. Nevertheless, the company would be subject to high annual production and holding costs of the overproduced units. Therefore, the higher the amount of inventory from overproduction, the greater the increase in earnings but the lower is cash flow from operations.

Consequent with the methods discussed above, the following regressions are drawn in order to estimate the abnormal level of each measure which in return will be taken as a proxy of real earnings management:

i. $$CFO_{it}/Asset_{i\,t-1} = \alpha_{i0} + \alpha_1\left(\frac{1}{Asset_{i\,t-1}}\right) + \beta_2\left(\frac{Sales_{it}}{Asset_{i\,t-1}}\right) + \beta_3\left(\frac{\Delta Sales_{it}}{Asset_{i\,t-1}}\right) + \varepsilon_{it}$$

j. $$PROD_{it} = \alpha_{i0} + \alpha_1\left(\frac{1}{Asset_{i\,t-1}}\right) + \beta_2\left(\frac{Sales_{it}}{Asset_{i\,t-1}}\right) + \beta_3\left(\frac{\Delta Sales_{it}}{Asset_{i\,t-1}}\right) + \varepsilon_{it}$$

k. $$DISC_{it} = \alpha_{i0} + \alpha_1\left(\frac{1}{Asset_{i\,t-1}}\right) + \beta_2\left(\frac{Sales_{it}}{Asset_{i\,t-1}}\right) + \beta_3\left(\frac{\Delta Sales_{it}}{Asset_{i\,t-1}}\right) + \varepsilon_{it}$$

Where CFO_{it} is cash flow from operation in period t for firm i;$PROD_{it}$ represents the production cost for firm i in period t (equal the sum of cost of goods sold and change in inventories); $DISC_{it}$ represents the discretionary expenditures in period t for firm I (equal the sum of R&D, Advertising and SG&A). The abnormal levels of CFO,PROD and DISC are computed as the difference between the actual values and the normal levels predicted from regressions i j and k.

Given sales level, firms that manage earnings upwards are expected to report the following:

- Unusually low cash flow from operations
- Unusually high production cost
- Unusually low discretionary expenses

In order to observe the total impact of real earnings management RM1 and RM2 are computed as follow:

l. $RM1 = A_{prod} - A_{Disc}$

m. $RM2 = -Acfo - Adisc$

Where Aprod, Acfo and Adisc are abnormal levels of production cost, cash flow from operations and discretionary expenses respectively. Adisc and Acfo are in negative signs since the lower these metrics are the more likely real earnings management is used. The reason why all three metrics cannot be merged together is because Aprod and Acfo are reversely correlated as explained above.

3.5.3. Comprehensive System GMM Panel regression:

The model used in this research is System GMM (Generalised Method of Moment) introduced by Arellano and Bover (1995) as an extension of Arellano and Bond (1991). This model was chosen as the OLS equation is subject to endogeneity which System GMM mainly deals with. According to Wooldridge (2010), endogeneity can appear if any of the following exists:

- Omitted variables: This problem arises when we want to control for one or more additional variables in the equation, but we cannot include them because of data unavailability or they are unobservable variables.

- Measurement error in the dependent or independent variable: Most empirical studies in business research use proxies for unobservable or difficult to quantify variables, any discrepancy between the true variable and the proxy leads to measurement error.

- Simultaneity (reversal causality): Simultaneity arises when at least one of the explanatory variables is determined simultaneously along with the dependent variable.

The consequence of this problem will be a correlation between the error term and the endogenous explanatory variable, resulting in bias in the OLS estimator. In respect to this study, a possible relationship between financial analysts and companies' managers is very likely to produce an endogeneity problem appearing in a shape of reversal causality. One example of this relationship is that managers might put pressure on forecasters to issue less optimistic forecasts in order to make it easier for the company to meet or beat analysts' forecasts. Another example is when analysts issue more favourable figures for managers in order to maintain their relationship and access private information. If this is true, an OLS (Ordinary Least Square) estimator will be biased. Since no pure instrument of earnings management was found, System GMM is employed relying on lagged variables as instruments of earnings management metrics. The main argument behind the System GMM approach is that it relies on lagged values being the best available internal instruments of the endogenous factors (in this case abnormal accruals and real earnings management) especially when external proxies are not available. Taking lagged values is very practical in the sense that they are highly representative of level variables, but independent of the level variables of earnings management (since a lagged variable cannot be affected by a future variable). In this case the lagged values of independent variables are correlated with present values but not with the error term (as long as they are not serially correlated). Furthermore, System GMM mixes values in level and first differences to deal with the heterogeneity. Due to the existence of first order autocorrelation (Arellano-Bond autocorrelation tests can be seen under each of the GMM tables 3.4,3.5,3.6 and 3.7), the lags that are used start from lag 2 and end lag 5. Ending lags at 5 is important to avoid the problem of over-identification of instruments (further tests also presented under the same tables).

It is worth noting that 2SLS (two stage least square) regression is avoided in this research due to two shortcomings. First, according to Blundell and Bond (1998) 2SLS is efficient under homoscedasticity. Nevertheless, in case of heteroscedasticity and if first differences are used, the differenced error terms might become less independent. Second, the instrumental-variables estimators are inconsistent if N (number of observations) is large and T (number of years) is fixed. Despite using 20 years in this research seems to be large enough, however, the number of companies is much greater (589 yearly average). Additionally, since the panel is unbalanced, a lot of firms do not have data throughout all the years which minimises T in front of N.

To test the main hypothesis, that earnings management increases the errors in earnings forecasts, the regression n.is estimated as follow:

n. $$|FE_{it}| = \alpha_{i0} + \beta_1|AA_{it}| + \beta_2|RM_{it}| + \beta_3 N_{it} + \beta_4 TV_{it} + \beta_5 Unc_{it} + \beta_6 BTM_{it-1} + \beta_7 ExcessROE_{it-1} + \beta_8 AG_{it-1} + \beta_9 EarningsD_{it-1} + \beta_{10} profitD_{it-1} + \beta_{11} DivD_{it-1} + \beta_{12} Year_{it} + \beta_{13} Industry_{it} + \varepsilon_{it}$$

Regression n uses absolute values of forecast error and earnings management variables in order to catch the general impact of the dependant over the independent. This regression is meant to test hypothesis 1. However, in order to test the rest of the hypotheses (from hypothesis 3.2 to 3.5) where behavioural information have a lot to explain, the signs of FE, AA and RM are released in regression o :

o. $FE_{it} = \alpha_{i0} + \beta_1 AA_{it} + \beta_2 RM_{it} + \beta_3 N_{it} + \beta_4 TV_{it} + \beta_5 Unc_{it} + \beta_6 BTM_{it-1} + \beta_7 ExcessROE_{it-1} + \beta_8 AG_{it-1} + \beta_9 EarningsD_{it-1} + \beta_{10} profitD_{it-1} + \beta_{11} DivD_{it-1} + \beta_{12} Year_{it} + \beta_{13} Industry_{it} + \varepsilon_{it}$

Where FE is forecast error as computed in equation a, AA_{it} is abnormal accruals estimated using regression f and RM_{it} is the estimated real earnings management variables RM1 and RM2 (used separately in different regressions) for company i in year t. This main regression also includes a number of control variables proposed in the literature and proved to be significantly related to forecast error. N_{it} is the natural logarithm of number of followers forecasting a company i in year t (Used by Das et al. (1998), Ciconne (2005), Cohen and Zarwin (2010)). This variable is expected to be positively related to forecast error as the greater the number of analysts the higher the competition is among forecasters. This is likely to lead to more speculative figures such as optimistic earnings forecasts.

$TV_{it}$is a proxy of Firm size and is computed as the natural logarithm of yearly trade volume. The explanatory power of this variable is to capture analysts' incentive to generate trading commissions based on trading volumes (Hayes, 1998) Due to multicollinearity issues between market capitalisation and number of followers, trade volume is used to offset the relationship between forecast error and firm size (Hayes (1998)). Since the smaller the firm the less information is accessible about it, it will be harder for an analyst to forecast smaller firms. If this is true, trade volume is expected to be negatively related to forecast error.

$Uncert_{it}$represents the uncertainty of company's performance calculated as the standard deviation of 12 months earnings forecasts (Gu and Wu (2003)). When company's earnings are less stable, it will become harder for analysts to accurately predict the performance thus forecast error is expected to increase. Das et al. (1998) argue that when earnings are less predictable, it represents a stronger incentive for analysts to issue optimistic forecasts to facilitate information acquisition from management.

Companies' lagged performance variables were also proved to be related to the accuracy of forecasts. Henderson and Marks (2013) highlight the importance of considering performance variables and state the following: "The underlying idea is that observation of the net profit margin implied by analyst forecasts provides a reference point from which earnings and revenue forecasts can be judged to be extreme and thus inaccurate" (Henderson and Marks (2013, p.8)). Ciconne (2005) considers lagged profit margin as an explanatory variable of forecast error based on the argument that it is harder to predict a future performance of a company that is losing. They report that profitable companies have smaller forecast error than losjng companies. Another way of measuring performance is through the past year earnings change rather than levelled profit margin. Coen et al. (2009) report that analysts forecast performance is much weaker for firms' that saw a decrease in earnings than those that saw an increase in earnings. Consistent with the literature, a variety of performance variables were included in this regression. $EarningsD_{it-1}$ is a dummy variable of last year company's earnings variation, having a value of 1 if earnings per share increased between t-2 and t-1 and 0 otherwise (Ciconne (2005)). $profitD_{it-1}$ is another dummy of performance taking 1 if the company's EPS was positive and 0 otherwise (Ciconne (2005)). Additionally, other performance variables were included such as BTM_{it-1} which is the lag of book to market value of company i in year t (So (2013)), $DivD_{it-1}$ which is a dummy of whether the company paid dividends last period or not (So (2013)) and AG_{it-1} which represents the asset growth between period t-2 and t-1 for firm i.

According to McNichols and O'Brian (1997), firms with good future prospectus are less subject to selection bias-induced optimism. To proxy for this bias, the analysis use $ExcessROE_{it-1}$ which is the difference between the company's return on equity and the median of industry's return on equity (Gu and Wu (2003)). All coefficients of performance variables are expected to have a negative sign due to the optimistic behaviour of forecasters following a good performance.

A descriptive statistics of the metrics calculated above and the rest of the variables used in the main regression are shown in table 3.2 below. The average of FE appears to be high with 31.3%, possibly because it's in absolute value. All proxies of earnings management are standardised by total assets. From one side, AA reports a mean of -1.2% suggesting that managers on average tend to manage earnings downwards using accruals. On the other side, Table 3.2 above shows positive averages of Adisc and Acfo (14.7% and 6% respectively) meaning that earnings are managed downwards consistent with the use of Abnormal Accruals. Only the average level of production costs had an opposite interpretation with a mean of 79.6%, suggesting that earnings are managed upwards using abnormally high production costs. This preliminary result (3 out of 4 metrics) doesn't mainly support the assumption that managers use earnings management in order to boost their companies' earnings except when it comes to the use of abnormal production cost. However, more detailed empirical analysis will follow to show the relationship between forecast error and each of the earnings management metrics.

Table 3.2 Descriptive statistics of all variables.

Variable name	Definition	N	Mean	Std. Dev.	Min	Max
FE	forecast error	10,201	0.313	0.380	0.00	1.357
AA	Abnormal accruals	7,572	-0.012	0.088	-0.30	0.277
ACFO	Abnormal CFO	8,883	0.060	0.096	-0.249	0.374
Aprod	Abnormal production Cost	7,252	0.796	0.718	-0.05	3.563
Adisc	Abnormal Discretionary expenditure	7,247	0.147	0.253	-2.653	3.551
BTM	book to market value	11,509	0.587	0.481	0.009	2.703
N	n. of followers	11,395	8.493	6.311	3	37.750
TV	Trade volume	10,772	663,551	2,912,460	10,000	99,000,000
AG	Asset Growth	9,485	0.115	0.295	0	1.703885
Uncertainty	Standard Dev of 12 month Forecasts prior to the announcement date	10,434	0.019	0.205	0	11.50155
ROE-excess	ROE minus median industry ROE	10,667	0.009	0.317	-1.5225	1.73625
EarningsD	Last year earnings increase dummy	8,495	0.74	0.439	0	1
ProfitD	Last year profit dummy	11,084	0.886	0.317	0	1
DivD	Last year Dividend dummy	11,075	0.894	0.308	0	1
sizecategory	1 for small companies, 2 for medium companies and 3 for big companies	11,770	2.013	0.712	**1**	**3**
SMALL	Dummy variable when market cap of a company in the lowest tercile distribution of market cap	2,906	24.6%	0.431	0	1
MED	Dummy when market cap falls between 25th and 75th percentile of the market cap distribution	5,801	49.3%	0.500	0	1
BIG	Dummy variable when market cap falls in the highest tercile of market distribution	3,063	26.1%	0.439	0	1

Table 3.3 Pearson's Correlation analysis between all variables

Variables	FE	Aaccruals	Acfo	Aprod	Adisc	N	TV	Uncert	BTM	excessroe	AG	earningsD	profitD	divD
FE														
Aaccruals	0.057***	1												
Acfo	-0.069***	-0.038*	1											
Aprod	-0.064***	-0.019	0.981***	1										
Adisc	-0.026*	0.138***	0.490***	0.570***	1									
N	-0.028*	-0.146**	0.103***	0.056***	-0.333***	1								
TV	0.076**	-0.074**	-0.010	-0.051***	-0.362***	0.589***	1							
UNCER	0.098***	0.064**	-0.018	-0.009	0.008	-0.051***	-0.005	1						
BTM	0.060**	-0.069**	-0.266**	-0.293***	-0.313*	-0.097***	-0.010	0.008	1					
excessroe	-0.156***	-0.058**	0.194***	0.207***	0.033***	0.129***	0.060***	-0.123***	-0.295***	1				
AG	0.002	0.040*	-0.008	0.043***	-0.068***	-0.004	-0.030***	0.011	-0.102***	0.056***	1			
earningsD	-0.038***	0.016	0.063**	0.114***	0.070***	-0.067***	-0.098***	-0.013	-0.137***	0.110***	0.110**	1		
profitD	-0.121**	-0.128*	0.142**	0.166***	-0.026***	0.106***	-0.034***	-0.069*	-0.125***	0.233***	0.167**	0.328***	1	
divD	-0.189***	-0.182*	0.176**	0.179***	-0.063***	0.176***	0.014**	-0.126*	-0.077*	0.319***	0.027*	0.049***	0.343***	1

*****Significant at 1% level, ** significant at 5% level, * significant at 10% level**

In order to catch the size effect on forecast error, companies are divided into three size categories using market capitalisation. Small companies are the ones with market cap belonging to the lowest tercile distribution of the total market cap. Medium size is when the market cap of companies falls between the 25^{th} and 75^{th} percentile in the market cap distribution. Big size companies are those that have a market cap within the highest quartile of the market cap distribution. The Pearson's correlation coefficients between all variables could be seen in table 3.3 (above). Forecast error is significantly positively correlated with abnormal accruals suggesting that an abnormal increase in accruals would lead to larger forecast error. Moreover, forecast error is negatively correlated with Acfo and Adisc and supporting the assumption that managers might cut discretionary expenses to boost earnings. However, the correlation coefficient between Acfo and Aprod is 0.98 and significant at 1% confidence level. This result is inconsistent with the theory since a higher level of production cost is expected to lead to lower levels of cash flow from operations as explained earlier. As expected, a strong positive correlation was found between TV and N since more traded companies are likely to be followed by more analysts. Furthermore, all performance variables (ExcessROE, EarningsD, ProfitD and DivD) had a negative significant correlation with forecast error except for AG. This result indicates that when a company performs well during a certain year, analysts appear to be more accurate when forecasting its earnings the following year.

3.6. Empirical results:

3.6.1. Testing hypothesis 3.1:

As stated earlier, equation n is used to test hypothesis 1 that the use earnings management in any form will increase the absolute value in earnings forecast error. Results from regression n can be seen in table 3.4. Fixed effect and System GMM estimators are compared in this table. Regression 1 and 2 use AA as a sole proxy of earnings management. As expected, abnormal accruals is positively affecting analyst forecast error with a coefficient 0.203 significant at 5% confidence level. Fixed effect coefficient still shows a positive relationship but lower coefficient of 0.12 also significant at 5%. The difference in the coefficients of fixed effect and System GMM is due to the possible endogeneity present in this analysis. Roodman (2012) also finds that fixed effect estimators are biased downwards in the presence of endogeneity. In addition to AA, RM1 is added in regressions 3 and 4 to represent real earnings management. While the positive impact of AA seems to be persistent, no significant relationship between RM1 and FE was found. This result suggests that forecasters are not affected by earnings management done through real activities. In other words, analysts appear to anticipate real activities applied during the fiscal year from overproduction or cutting discretionary expenses. In regression 5 and 6 RM1 is replaced by RM2 to see whether an abnormal change in cash flow from operations and discretionary expenses could have any impact on forecast errors. Similar to Rm1, no significant relationship was found between RM2 and FE. The fact that real earnings management doesn’t seem to be affecting forecast error could be due to the timing at which real activities are done. The decisions taken by managers to manage earnings using real activities are usually done throughout the fiscal year allowing analysts to analyse and anticipate these adjustments. While real earnings management shift the reported earnings at the end of the year, earnings forecasts have already been changed in the same direction as the real earnings following the adjustments. As a result, forecast error would become smaller and hypothesis 1 would be insignificant. Contrarily, earnings management based on accruals is usually done by the end of the fiscal year specifically after closing the books. Since this type of adjustments is based on management accounting, managers are careful not to be very aggressive thus they wait until the end to know which estimated accounts they are able to tweak and by how much. This will leave less room for analysts to anticipate such adjustments and forecast error will become larger[8]. Table 3.4 below also presents Arellano and Bond’s test of autocorrelation (at order 1 and 2). As explained in section 3.5.3, the lags instruments used start from lag 2 based on the existence of autocorrelation at first order AR(1). Moreover, they are capped at lag 5 to avoid the problem of over-identification which is very common when using many instruments in GMM.

[8] Further analysis was applied to check whether the introduction of the Sarbanes-Oxley act (2002) in the US had any impact on the results in the UK market, but no significant difference was found. A possible explanation this is that many British companies appear to be listed through ADRs in the US market. Hostak and Lis (2013) report how firms holding ADRs avoided the costs implied by the SOX act.

Table 3.4 Regression analysis of FE forecast error and earnings management AA, RM1 and RM2. $|FE_{hT}| = \frac{F_{ht}-E_t}{|E_t|}$ F is the monthly consensus forecasts, E is the realised earnings per share, AA is abnormal accruals, RM1 and RM2 are the first and second proxies of real earnings management respectively.

|FE|	**1**	**2**	**3**	**4**	**5**	**6**
VARIABLES	**Fixed Effect- AA**	**GMM - AA**	**Fixed Effect-AA and RM1**	**GMM - AA and RM1**	**fixed Effect-AA and RM2**	**GMM - AA and RM2**
	Coef (std Error)	**Coef (std Error)**	**Coef (std Error)**	**Coef (std Error)**	**Coef (std Error)**	**Coef (std Error)**
| AA |	0.120**	0.203**	0.175**	0.199*	0.116	0.125
	(0.0540)	(0.0970)	(0.0755)	(0.109)	(0.0788)	(0.114)
|RM1|			-0.00437	-0.0256		
			(0.0171)	(0.0229)		
|RM2|					0.105	0.123
					(0.0832)	(0.0869)
N	-0.000361	-0.0136	-0.000526	-0.0287	-0.000432	-0.0276
	(0.00115)	(0.0162)	(0.00116)	(0.0239)	(0.00116)	(0.0239)
TV	0.0218***	0.0237***	0.0223***	0.0289***	0.0219***	0.0279***
	(0.00665)	(0.00801)	(0.00670)	(0.0106)	(0.00669)	(0.0107)
Uncertainty	0.113***	0.140***	0.113***	0.139***	0.113***	0.141***
	(0.0188)	(0.0344)	(0.0188)	(0.0339)	(0.0188)	(0.0351)
BTM	0.0650***	0.0547***	0.0657***	0.0458**	0.0650***	0.0477**
	(0.0127)	(0.0177)	(0.0128)	(0.0192)	(0.0128)	(0.0191)
excessroe	-0.0460***	-0.0392***	-0.041***	-0.0351***	-0.0460***	-0.037***
	(0.00767)	(0.0109)	(0.00773)	(0.0113)	(0.00774)	(0.0114)
AG	0.0374***	-0.00240	0.0310**	-0.00663	0.0358***	-0.00700
	(0.0115)	(0.0143)	(0.0121)	(0.0167)	(0.0119)	(0.0167)
EarningsD	0.00138	-0.00613	0.000173	-0.00548	0.00118	-0.00672
	(0.00684)	(0.00690)	(0.00686)	(0.00689)	(0.00685)	(0.00688)
profitD	-0.0393***	-0.0338**	-0.041***	-0.0369**	-0.0400***	-0.0396**
	(0.0123)	(0.0165)	(0.0124)	(0.0172)	(0.0123)	(0.0169)
divD	-0.0278	-0.106***	-0.0299	-0.0951***	-0.0287	-0.099***
	(0.0188)	(0.0282)	(0.0189)	(0.0278)	(0.0189)	(0.0280)
Observations	5,190	5,592	5,190	5,548	5,191	5,549
R-squared	0.071		0.071		0.070	
Arellano-Bond AR(1)		0.002		0.000		0.000
Arellano-Bond AR(2)		0.193		0.132		0.211
Hansen Overidentification test		0.136		0.136		0.110
Sargan-Hansen Exogeneity test		0.696 (AA)		0.665 (for AA) 0.270 (for RM1)		0.706(AA)-0.173(RM2)

*****Significant at 1% level, ** significant at 5% level, * significant at 10% level**

Consequently, Hansen's over-identification test is presented in the table, with a P-value of J statistics above 10% in all three GMMs, this confirms that the null cannot be rejected assuring the joint validity of the specified instruments. According to Baum (2006), the Hansen test of overidentification evaluates the entire set of overidentifying restrictions. However, to make sure about the validity of a subset of instruments, the Sargan-Hansen difference exogeneity test can be used. Results of this test can also be seen under the GMM figures in the table, giving a value for the subset of instruments of the endogeneous factors (AA, RM1 and RM2). The test confirms the exogeneity of the subsets as the P-values exceed 10% and the null hypothesis cannot be rejected. Similar results about the autocorrelation, overidentification and exogeneity can be found in each of the GMM tables performed in this chapter.

Regarding the rest of the variables, the number of followers N wasn't found to have any impact on forecast error. As this could be due to the correlation between trade volumes (TV) and N, TV was withdrawn from the regression (in a separate test) but this robustness test didn't change anything and N remained insignificant.

Nevertheless, trade volume appears to be positively and significantly affecting forecast error with a coefficient of 2.3% in regression 2. This result suggests that analysts would make more error when forecasting firms that are traded more. The Uncertainty of firms' earnings has a positive impact on forecast error. The coefficient is 0.14 significant at 1% confidence level. This result is sensible since more volatile earnings are harder to predict. Regarding the performance variables, if a company makes a profit the previous year, forecast error decreases the following year. This is proved by the negative significant coefficient between profitD and FE (-0.0338 significant at 5%). Similarly, the coefficient of ExcessRoe is -0.0392 is significant at 1% level suggesting that if a company performs better than the industry median earnings, forecast error decreases the following year. The third significant performance variable was the dividend Dummy (DivD). The relationship between FE and DivD appears to be negative and significant at 1% stating that if a company announces dividends the previous year, forecast error decreases the following year. This is consistent with Ciconne (2005) who find that losing firms are harder to predict. Despite finding the association between forecast error and earnings management being significant, however, using absolute values cannot fully explain why earnings management is positively affecting forecast error. Is it because earnings are increasing surprisingly due to earnings management making the forecasts fall below actual earnings?

Or is it simply because analysts insist on being overly optimistic or pessimistic making the error always big? In order to read between the lines and understand better the reasons behind the forecast error, the next sections allow for forecast error and earnings management variables to be signed. The new hypothesis will explain whether boosting earnings will make forecasters look pessimistic, or managing earnings downwards will make forecasters look extremely optimistic.

3.6.2. Testing hypothesis 3.2:

Should earnings management be used in order to decrease earnings (Big Bath or earnings smoothing), forecast error is expected to increase making analysts look more optimistic. Table 3.5 displays results of regression O that includes optimistic forecasts only (when FE is positive) and negative AA, RM1 and RM2 assuming they are proxies of negative use of earnings management used to decrease earnings. This regression aims to test hypothesis 2 stating that negative use of earnings management should lead to more optimistic forecasts. Results in table 3.5 confirms hypothesis 2. The relationship between AA and FE is now turned to be negative with a coefficient of -0.203 significant at 10% level. This negative coefficient indicates that the higher the use of earnings management (a more use of abnormal accruals in a negative sign) the higher the forecast error is. The fact that earnings management this time is used to decrease earnings, the downward shift in reported earnings opens a gap between the forecasts and earnings making analysts look more optimistic.

Once more, real earnings management RM1 and RM1 were not found to be significant. Nevertheless, the main assumption made by Roychowdhury (2006) is that real earnings management is used to boost earnings. This assumption holds after testing hypothesis 2 since it includes only negative forms of earnings management assuming it's used to decrease earnings. The number of analysts N continues to be insignificant. The impact of trade volume on forecast error has disappeared. This is somehow unexpected since analysts are more likely to issue optimistic forecasts for firms that are highly traded. The negative coefficients of performance variables excessroeD and divD remain the same in this test implying that a positive last year's performance would make analysts less optimistic the following year. The coefficient of Uncertainty was large and highly significant indicating that the more uncertain the company, the higher the forecast error is.

Table 3.5 Regression analysis of positive forecast error FE and negative earnings management AA, RM1 and RM2. $FE_{hT} = \frac{F_{ht}-E_t}{|E_t|}$ F is the monthly consensus forecasts, E is the realised earnings per share, AA is abnormal accruals, RM1 and RM2 are the first and second proxies of real earnings management respectively.

Dep : FE > 0	**1**	**2**	**3**	**4**	**5**	**6**
VARIABLES	**fixed-AA Coef (std error)**	**GMM-AA Coef (std error)**	**Fixed-AA and RM1 Coef (std error)**	**GMM-AA and RM1 Coef (std error)**	**fixed-AA and RM2 Coef (std error)**	**GMM-AA and RM2 Coef (std error)**
AA < 0	-0.242*	-0.203*	-0.169	-0.196*	-0.100	-0.208**
	(0.141)	(0.110)	(0.183)	(0.105)	(0.165)	(0.0894)
RM1 < 0			-0.0250	0.0101		
			(0.0210)	(0.0223)		
RM2 < 0					-0.176	0.0619
					(0.140)	(0.106)
N	-0.00195	0.0109	-0.00198	0.0324	-0.000289	0.0286
	(0.00253)	(0.0231)	(0.00335)	(0.0301)	(0.00324)	(0.0285)
TV	0.0165	0.0140	0.0150	0.00648	0.00948	0.00690
	(0.0155)	(0.00850)	(0.0189)	(0.0104)	(0.0188)	(0.0101)
Uncertainty	0.542	1.316***	0.534	1.546*	0.549	1.493*
	(0.563)	(0.501)	(0.521)	(0.803)	(0.526)	(0.788)
BTM	0.105***	0.0377	0.0882*	0.0169	0.0977**	0.00891
	(0.0385)	(0.0274)	(0.0476)	(0.0299)	(0.0480)	(0.0327)
excessroeD	-0.0426**	-0.0275*	-0.0453**	-0.0296	-0.0523**	-0.0316*
	(0.0174)	(0.0157)	(0.0212)	(0.0201)	(0.0217)	(0.0183)
AG	0.0731**	0.00606	0.0463	0.00250	0.0633*	-0.000807
	(0.0301)	(0.0223)	(0.0370)	(0.0288)	(0.0370)	(0.0271)
EarningsD	-0.00287	0.00364	0.00289	0.00343	0.000200	0.00486
	(0.0141)	(0.0117)	(0.0174)	(0.0152)	(0.0170)	(0.0155)
profitD	-0.0359	-0.00383	-0.0359	-0.0163	-0.0449	-0.0196
	(0.0283)	(0.0270)	(0.0337)	(0.0295)	(0.0337)	(0.0298)
divD	-0.107	-0.0858*	-0.0975	-0.119**	-0.111	-0.112**
	(0.0801)	(0.0511)	(0.0904)	(0.0534)	(0.0898)	(0.0519)
Observations	3,229	2,457	3,259	2,353	2,330	2,486
R-squared	0.078		0.079		0.076	
Observations	5,190	5,592	5,190	5,548	5,191	5,549
Arellano-Bond AR(1)		0.01		0.003		0.003
Arellano-Bond AR(2)		0.854		0.718		0.788
Hansen Overidentification test		0.291		0.504		0.313
Sargan-Hansen Exogeneity test		0.922(for AA)		0.743 (for AA) 0.73 (for RM1)		0.490AA)-0.371(RM2)

*****Significant at 1% level, ** significant at 5% level, * significant at 10% level**

Table 3.6. Regression analysis of negative forecast error FE when earnings management AA, RM1 and RM2 are positive. $\boldsymbol{FE_{hT}} = \frac{F_{ht}-E_t}{|E_t|}$ F is the monthly consensus forecasts, E is the realised earnings per share, AA is abnormal accruals, RM1 and RM2 are the first and second proxies of real earnings management respectively.

Dep : FE < 0	**1**	**4**	**2**	**5**	**3**	**6**
VARIABLES	**fixed**	**GMM-AA**	**Fixed- AA and RM1**	**GMM- AA and RM1**	**fixed- AA and RM2**	**GMM- AA and RM2**
	Coef (std error)	**Coef (std error)**	**Coef (std error)**	**Coef (std error)**	**Coef (std error)**	**Coef (std error)**
AA > 0	-0.00577	-0.382***	-0.0401	-0.597***	-0.00338	-0.499***
	(0.0527)	(0.125)	(0.0653)	(0.168)	(0.0695)	(0.174)
RM1 > 0			-0.000538	0.0821		
			(0.0103)	(0.0943)		
RM 2 > 0					-0.0148	0.122
					(0.0312)	(0.131)
N	0.00205	-0.00194	0.00113	0.000158	0.000920	0.000197
	(0.00218)	(0.00380)	(0.00148)	(0.0433)	(0.00165)	(0.0420)
TV	0.00203	-0.00991	-0.00602	-0.0114	0.00107	-0.0233
	(0.00602)	(0.0195)	(0.00541)	(0.0191)	(0.00550)	(0.0203)
Uncertainty	-1.008**	-0.211	-0.721**	-0.0415	-1.008**	-1.396
	(0.402)	(0.672)	(0.345)	(0.741)	(0.461)	(1.340)
BTM	-0.0204	-0.0612*	-0.0338*	-0.0102	-0.0383	-0.0525
	(0.0135)	(0.0338)	(0.0180)	(0.0406)	(0.0232)	(0.0514)
excessroeD	0.00353	-0.0165	0.000732	-0.00234	0.00144	-0.0424
	(0.00703)	(0.0186)	(0.00794)	(0.0206)	(0.00911)	(0.0269)
AG	0.0109	-0.0149	0.00611	0.0634	-0.00781	-0.0454
	(0.0137)	(0.0275)	(0.0147)	(0.0449)	(0.0158)	(0.0416)
EarningsD	0.00200	0.0181	-0.00360	0.0450**	-0.00173	0.0558**
	(0.00630)	(0.0164)	(0.00797)	(0.0222)	(0.00791)	(0.0250)
profitD	-0.00357	0.0812**	0.00855	0.0587	-0.00548	0.0619
	(0.0186)	(0.0387)	(0.0274)	(0.0586)	(0.0240)	(0.0560)
divD	-0.0107	0.0378	-0.0412	-0.0939**	-0.0448*	-0.0740
	(0.0265)	(0.0413)	(0.0253)	(0.0462)	(0.0234)	(0.0583)
Observations	3,688	4,262	4,176	4,642	4,057	4,593
R-squared	0.185		0.157		0.322	
Arellano-Bond AR(1)		0.192		0.067		0.028
Arellano-Bond AR(2)		0.874		0.424		0.770
Hansen Overidentification test		0.331		0.913		0.949
Sargan-Hansen Exogeneity test		0.425 (AA)		0.827 (for AA) 0.994 (for RM1)		0.877AA)- 0.997(RM2)

*****Significant at 1% level, ** significant at 5% level, * significant at 10% level**

3.6.3. Testing hypothesis 3.3:

Building on the argument set in hypothesis 2 that managing earnings management downwards lead to higher forecast error, this section studies the impact of positive earnings management on negative forecast error (pessimistic forecasts). If it is true that one of the main incentives to use earnings management is to boost earnings, increasing earnings could lead to negative forecast error since earnings are driven upwards and analysts are assumed to be uninformed about earnings management.

More specifically, Hypothesis 4 examines the idea that positive AA, RM1 and RM2 should lead to more negative FE.

The coefficients shown in Table 3.6 support hypothesis 4. GMM estimator results in a negative coefficient of AA of -0.382 significant at 1% confidence level. After RM1 and RM2 were added, the AA coefficient changed respectively to -0.597 and -0.499 but stayed highly significant. Contrarily, real earnings management variables RM1 and RM2 were insignificant leading us to the initial interpretation that forecasters were able to anticipate real earnings management but not accruals management. This result supports the main argument that when earnings management (specifically accruals-based) is used to boost earnings, analysts seem to look pessimistic as their forecasts fall below the reported earnings.

3.6.4. Sensitivity analysis-hypothesis 3.5:

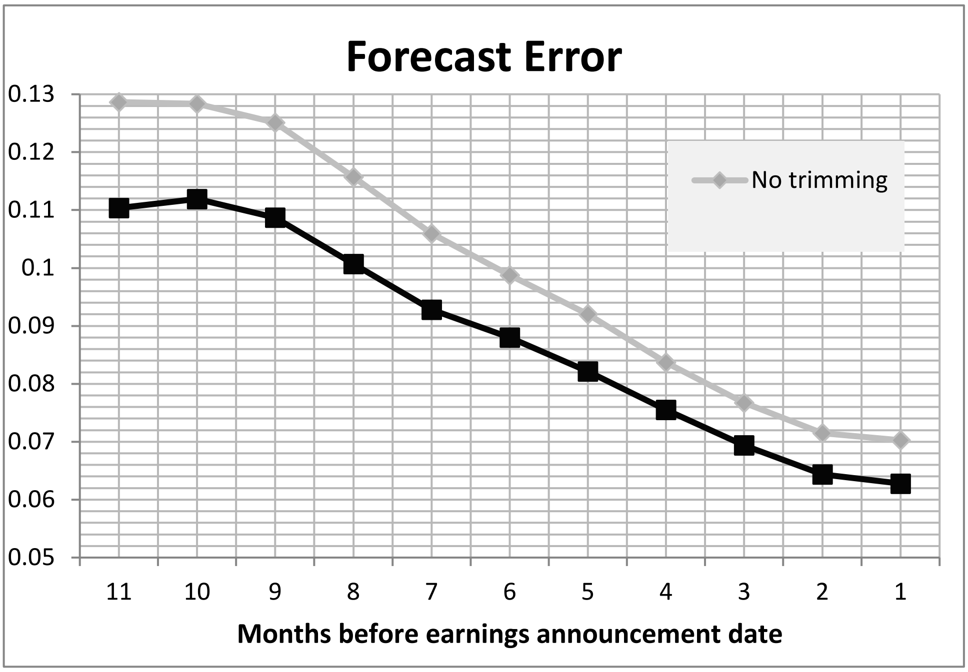
It is important to mention again the main assumption that no insider information is accessible and analysts are rational in conducting their forecasts. Nevertheless, all previous hypothesis testing would be unreliable if analysts are proved to be irrational or if for any reason insider information was leaked. One very important example studied in the literature is when managers try to put pressure on analysts to lower their earnings forecast allowing them to avoid a negative surprise (De Bont and Thaler (1990, Capstaff, Paudyal and Rees (1995), Capstaff, Paudyal and Rees (2001)).

To do so, analysts would have to revise their forecasts downwards the closer they approach the earnings announcement date. Analysts' motivation in this case could be maintaining a good relationship with insiders in order to access more private information in the future.

The movement of forecast error throughout 11 months before earnings announcement date is illustrated in figure 3.1. The sample used for figure 3.1 includes positive forecast errors only indicating that only optimistic forecasts are used. The lines of trimmed and untrimmed data clearly show a systematic decrease in the forecasts towards the end of the year.

H5: After excluding biased forecasts, the use of earnings management will increase analyst forecast error.

Figure 3.1 Variation of forecast error from 11 to 1 month prior to earnings announcement date, forecast error is the difference between consensus forecasts and actual earnings per share divided by absolute value of actual earnings per share.



In this specific case, biased forecasts are more accurate than the rest of the forecasts due to information leakage reaching the analysts especially towards the end of the period. Therefore, using a sample net of biased forecasts is expected to show a higher impact of earnings management on forecast error. From a different perspective, forecasters are no more mislead by earnings management since forecasts are no more random.

A sample portfolio of suspect firms is created to exclude biased forecasts. A biased forecast of a certain firm is a monthly optimistic forecast that was revised downward by more than 20% from 6 to 1 month before earnings announcement date. For example, assuming a firm's announcement date is December of every year. The firm's yearly forecast will be excluded if its monthly EPS forecast was downgraded by more than 20% between June and December. The choice of the last 6 months window was due to two factors. First, the probability that forecasters change significantly their forecast is lower in the second half of the year compared to the first half unless an outside variable emerged surprisingly (one of which is a request from insiders). Second, the first half of the season is usually harder to predict and it is less likely that managers would ask analysts to pull down their forecasts with half of the period is yet to be completed.

Table 3.7 Regression analysis of forecast error over abnormal accruals before and after exclusion of biased forecasts. $|FE_{hT}| = \frac{F_{ht}-E_t}{|E_t|}$ F is the monthly consensus forecasts, E is the realised earnings per share, AA is abnormal accruals, RM1 and RM2 are the first and second proxies of real earnings management respectively.

Dep :| FE |	1	4
	Before Exclusion	After Exclusion
VARIABLES	Coef (std error)	Coef (std error)
| AA |	0.203**	0.312***
	(0.0970)	(0.0966)
N	-0.0136	-0.000334
	(0.0162)	(0.00224)
TV	0.0237***	0.0280***
	(0.00801)	(0.00919)
Uncertainty	0.140***	0.308
	(0.0344)	(0.225)
BTM	0.0547***	0.0573***
	(0.0177)	(0.0195)
excessroeD	-0.0392***	-0.0364*
	(0.0109)	(0.0213)
AG	-0.00240	-0.00400
	(0.0143)	(0.0157)
EarningsD	-0.00613	0.00573
	(0.00690)	(0.00693)
profitD	-0.0338**	-0.0379**
	(0.0165)	(0.0170)
divD	-0.106***	-0.0691**
	(0.0282)	(0.0311)
Observations	5,592	4,023
Arellano-Bond AR(1)	0.002	0.00
Arellano-Bond AR(2)	0.193	0.162
Hansen Overidentification test	0.136	0.218
Sargan-Hansen Exogeneity test	0.696	0.361

*****Significant at 1% level, ** significant at 5% level, * significant at 10% level**

Table 3.7 shows results of the sensitivity analysis before and after exclusion of the suspect forecasts. As expected, the coefficient of AA is highly significant and increased from 0.203 to 0.312 after excluding biased forecasts. The result suggests that abnormal accruals have a higher impact on forecast error after excluding biased forecasts. In other words, earnings management have less impact when part of the overall forecasts is biased.

Furthermore, the second main assumption in this study is that managers do not manage earnings upwards in order to meet or beat analysts' forecasts. Releasing this assumption would lead to a reversal causality between earnings management and analyst forecast error. Many studies suggest that high public expectation encourages managers to manage earnings upwards (Burgstahler and Eams (2006), Caramanis and Lennox (2008)). Figure 3.2 illustrates the distribution of firm-years surrounding intervals of forecast error from -100% to +100%. This figure shows that the distribution is skewed to the right, implying that most forecast errors are positive. This means that forecasters are optimistic in general as the majority of forecasts fall above EPS. Alternatively, Roychowdhury (2006) states that managers engage in earnings management mainly to avoid losses. The later found evidence that the benchmark for managers is to report at least zero income before extraordinary items. Figure 3 shows a clear difference in the number of companies that report 0 or greater earnings and the ones reporting losses. This difference confirms Roychowdhury's findings.

Although figures 2 and 3 don't provide clear-cut evidence about the direct incentives behind earnings management, however, they are used in this research to see whether there could be reversal causality between earnings management and forecast error. While companies do not appear to be reporting earnings that meet or beat the forecasts, their priority lies in avoiding losses. They appear to be overwhelmingly reporting earnings at zero or just above. These findings diminish the impact of public expectation on earnings management and strengthen the reliability of the technical analysis.

Figure 3.2 Distribution of firms-years over forecast error depending on the level of forecast error from -100% to +100%, forecast error is the difference between consensus forecasts and actual earnings per share divided by absolute value of actual earnings per share

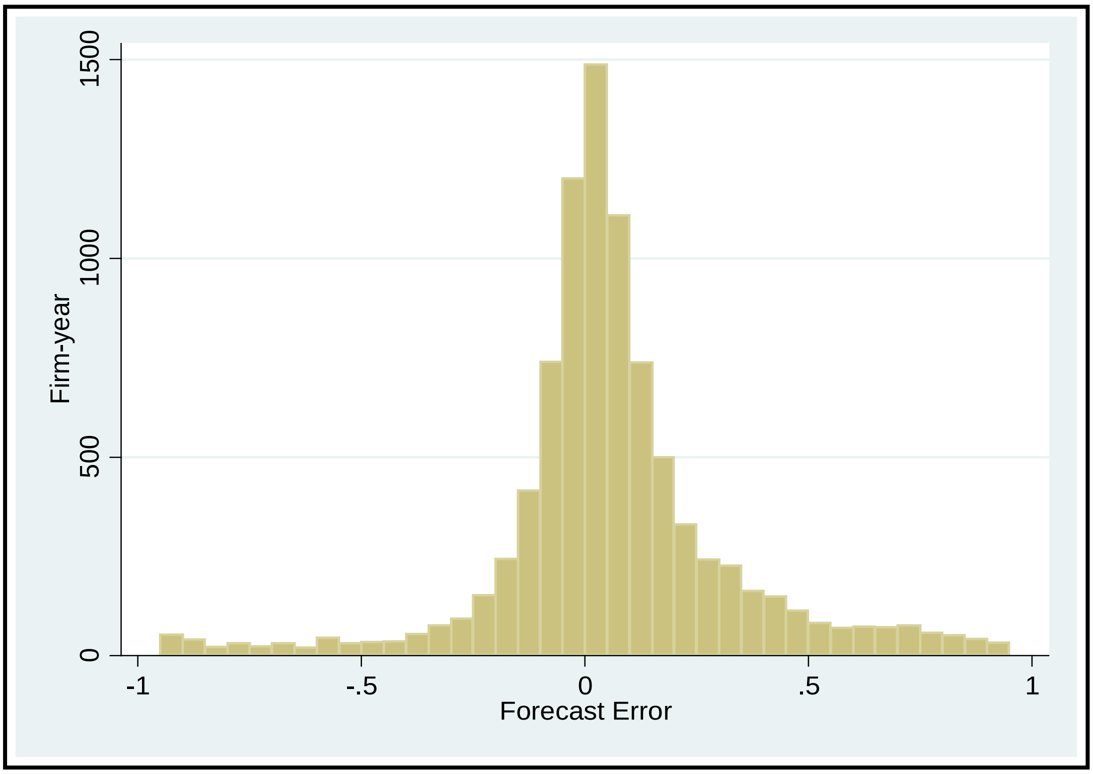
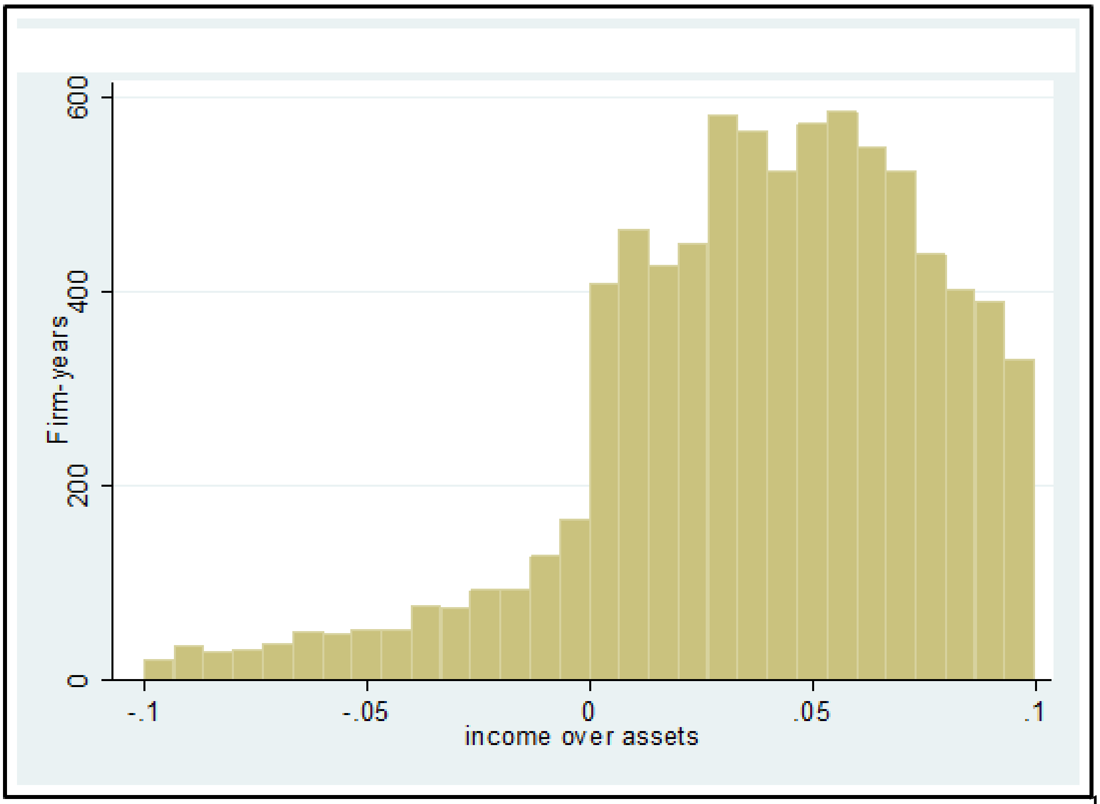


Figure 3.3 Distribution of firms-years over IBEI/assets, IBEI is the income before extraordinary items and assets is total assets.



3.7. Conclusion

This chapter argues that analysts' forecast error is affected by earnings management. Earnings management is the procedure of managing the discretionary variables affecting a company's earnings in order to make it look better, favourable, stable or sustainable. More precisely, managers could possibly manage their companies' earnings upwards to avoid losses, meet public expectations or to seek financial bonuses. They may also manage earnings downwards to smooth out earnings over a set of financial periods or take a big bath (report all possible losses in one period since a negative news cannot be avoided in any way). These techniques are employed using accruals-based or real activities earnings management. One the one side, accruals management is done through recognition of sales not yet delivered, timing gains or losses, estimation of pension liabilities, capitalisation of leases and market expenses and inventory methods. On the other side, real earnings management is done by adjusting real operational activities such as reducing R&D and advertising expenditures, sales acceleration and overproduction. Assuming that managers apply this manipulation internally and secretly, there is a big probability that such unanticipated alteration will make forecast errors look larger. Accordingly, this study examines the impact of earnings management on forecast error. There exists a lot of studies that link managers with analysts forecasts (Richardson et al. (2004), Mest and Plummer (2003)…). However, to our knowledge, the causal effect of earnings management on forecast error has never been covered before.

Using a UK sample of FTSE all share companies from 1993 to 2013, earnings management appear to be positively affecting analysts' forecast error. After controlling for number of control variables such as analysts following, size, earnings uncertainty, trade volume and a set of performance variables, this positive impact appears to be driven by accruals earnings management and not real earnings management. A possible explanation to this phenomenon is that managers modify real activities to manage earnings throughout the fiscal year which could be spotted by analysts earlier. However, accruals based earnings management is mainly done secretly after closing the books by the end of the fiscal year leaving analysts with almost no time to anticipate such changes.

Nevertheless, knowing that analysts' forecasts are part of the market expectation which is one of the motives behind earnings management, a possible reversed causality between earnings management and analysts forecast could be present. Accordingly, this requires extra measures in order to control for the endogeneity problem. GMM estimators were seen as the best fit to control for such problem using lagged values as valid instruments. After breaking down the forecasts into optimistic and pessimistic, GMM coefficients show that optimistic forecasts are positively affected by the negative use of earnings management (when earnings are managed downwards). This is due to the unexpected fall of earnings per share making forecasters look optimistic. Moreover, when earnings management is used to boost earnings, reported earnings look higher than usual, surpassing the forecasts and making analysts look pessimistic. Furthermore, robustness checks show that managers focus mainly on avoiding losses rather than meeting or beating analysts' forecasts. Apart from earnings management, loss companies appear to have bigger forecast error than profit companies, which is reasonable since loss companies are harder to predict (Ciconne (2005)).

Based on the above documentation, this chapter shows that external factors such as earnings management explain a major part in analysts' forecast error. Consequently, It stresses that analysts cannot be branded as extremely optimistic simply because their forecasts appear to be so different from the realised earnings. By proving so, this research highlights on the importance of tighter accounting standards and audit control to enforce complete transparency on public companies.

Chapter 4:

Analyst forecast error and Investor sentiment in cross sectional returns.

Chapter 4: Analyst forecast error and Investor sentiment in cross sectional returns.

Abstract:

Financial analysts are considered to be overall optimistic regarding their forecasts in most of the financial markets. At the same time, according to behavioural scholars, Investor Sentiment tends to be highly correlated with stock returns. Although the incentives and characteristics behind both behavioural biases may vary between the two market participants, it's very likely that one contributes to the other. This research studies whether financial analysts' error is related to investor's sentiment in the UK. Additionally, it examines how Investor sentiment, as a function of forecast error, affects stock return and the value premium phenomenon. Using all companies listed on London Stock exchange from 1992 until 2015, results show that analysts are overall optimistic. Furthermore, analysts releasing higher than average earnings per share forecasts lead to higher sentiment levels. While stock returns are significantly positively affected by sentiment levels, small stocks, growth stocks and stocks with weak profitability are more prone to sentiment shifts than value, large and stocks with robust profitability. This research highlights how bias in analysts' forecasts, reflected in the market sentiment, can lead to serious effects on the financial markets.

Chapter 4: Analyst forecast error and Investor sentiment in cross sectional returns.

4.1. Introduction

The previous chapters discuss two important aspects of analysts' earnings forecasts. The first one is the magnitude and direction of the forecast error and whether analysts show any sign of bias. The second one focuses on the external factors that affect the forecast error and in specific earnings management. This chapter takes the topic a step further to investigate the implications of forecast error on the stock market. Based on the definition of forecast which is the expectation of market participants, it examines the consequences of forecast error from a behavioural finance perspective.

Behavioural scholars in finance show a strong belief in sentiment as a major player in stock markets (Brown and cliff (2005), Baker and Wurgler (2006)). Market's expectation is a key factor in their argument regarding the existence of sentiment. According to Brown and Cliff (2004, p. 2), "Sentiment represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever average may be". This leads to divergence from the intrinsic value making market prices look vulnerable and prone to behavioural bias. Many aspects in finance have been investigated from a sentiment perspective. Daniel et al. (1998) suggest that market price momentum is partially driven by investor's overconfidence. Schmelling (2009) and Baker and Wurgler (2006) find that investor sentiment affects negatively future stock returns. Bergman and Roychowdhury (2008) argue that a firm's board is likely to change its disclosure policies depending on the market sentiment level.

In light of this matter, one cannot talk about market expectations without mentioning analyst forecasts. Financial analysts are an important source of information briefing the market with rich analysis and recommendations on a daily basis. Such source had a fare share of academic studies investigating its role and consequences. Most of previous studies report that analysts are overall optimistic regarding companies' future earnings (Capstaff et al. (2001), Gu and Wu (2003), Easterwood and Nutt (1999), Ciconne (2005), Larocque (2013)). Capstaff et. Al. (1995) argue that financial analysts might have the incentives to issue optimistic forecasts in order to increase the trading volumes generated after their forecasts. Abarbanel and Bernard (1992) finds that stock prices drift after earnings announcement are partially driven by inefficient forecasts made throughout the year. Mest and Plammer (2003) explain that optimism in analysts' forecasts facilitate the access to management's private information specially for hardly predictable firms. Baron, Biard and Liang (2013) focused on the timing of the analyst forecast depending on its type. They found that a pessimistic forecast is issued later than the other forecasts on average, which may explain why the last quarter of a fiscal year is less optimistic in terms of earnings forecast.

Consequently, this chapter investigates the association between forecast error, market sentiment and the value premium anomaly. More precisely, it starts by testing whether the forecast error made by financial analysts is a major component of sentiment in London Stock exchange. The idea is that when forecast error is positive, that is having an optimistic forecast, sentiment is likely to be high due to the high expectation been built by analysts. Sentiment, thereafter a function of forecast error, plays an important role in affecting stock returns documented in previous studies. The main argument in this analysis is that the reaction of stock prices can hardly be attributed to sentiment levels on the long run, in the sense that a fast-integrated market reflects the sentiment proxies very quickly making its impact evident on a short-run. Based on this argument, forecast error is believed to be play a big role in affecting short-term stock returns. Furthermore, as the nature of growth firms is different than value firms specially when it comes to forecasting, the relationship between investor sentiment and the long standing value premium phenomenon will also be examined. The value premium is a well-documented phenomenon where value stocks appear to earn higher returns than growth stocks (Fama and French (1992)). Why this phenomenon occurs is an open debate between scholars and professionals alike. This study contributes to the literature by introducing forecast error as a major player in explaining the value premium. The analysis also attempts to see how stock returns and the value premium behave in low and high sentiment moments.

Following Baker and Wurgler (2006), sentiment index is estimated using principal component analysis based on seven proxies: Forecast error, market turnover, number of IPOs, return on first day of IPO, Share of equity issuance, the dividend premium and the discount on closed-end mutual funds. The sample starts from January 1992 to December 2015 and covers all companies listed in London stock exchange. Analysts' forecasts were collected using IBES dataset available on Thomson Datastream. The rest of the data is collected from different databases including Bloomberg Terminals, Thomson Reuters Eikon and Worldscope databases.

Results show that forecast error is a major component of market sentiment and they are positively correlated. Contrary to Baker and Wurgler, Brown and Cliff (2005) and Baur, Quintero and Stevens (1996) who finds that future stock returns are negatively affected by sentiment levels, results in this research show that short term stock returns are positively affected by sentiment levels. Stock returns during high sentiment levels are higher than the ones during low sentiment levels. Furthermore, the value premium shrinks significantly when sentiment become high. This is due to the significant impact of sentiment on growth companies rather than value companies. As a result, small stocks, growth stocks and stocks with weak profitability are more prone to sentiment shifts than value, large and stocks with robust profitability. Such result contradicts with Brown and Cliff (2005) who report that Sentiment only affects large and institutional companies. These findings support the theory that growth firms are harder to value thus show a significant positive change when sentiment shifts from low to high.

The remaining of the chapter comes as follow: the second section discusses the background, literature and rational of the study. The third section explains the sample and methodology used. The fourth section navigates through discussions and interpretations. The fifth section presents a robustness check and the last section concludes.

4.2. Background and Literature Review

4.2.1. Forecast error and Stock returns

The wide roles undertaken by financial analysts in the stock market allowed finance scholars to explore and investigate diverse cases associated with behavioural finance, corporate finance, asset pricing and many more. Different aspects were discussed in the previous chapters related to the topic of analysts' forecast error. As stated above, this chapter will take a look at a likely consequence of forecast errors done by financial analysts which is the famous phenomenon of "Value premium". However, before reviewing the value premium literature, it is worth discussing some important consequences of forecast error in the stock market particularly asset pricing reported in previous studies.

Bernhard and Campello (2007) report that following downward forecast revisions, abnormal returns appear to be large following earnings announcement. Bernhard and Campello claim that this is true because as aggregate analysts revise their forecast downwards, the probability of getting positive surprise after the announcement increases (probability of having the actual earnings per share being higher than the forecasted earnings per share). The authors claim that such systematic downward revisions are very likely being managed by the firms' board themselves by "talking-down" analysts' forecasts and this claim is supported by few results. First, a greater positive earnings surprise appears to have a significant positive impact on stock returns. Second, firms that successfully manage their earnings forecasts downwards in the last two weeks before the earnings announcement date earn more than double the stock returns than the ones that don't. Third, firms that still have a positive earnings surprise at the end of the year but without having a downward forecast revisions trend report smaller abnormal returns than the ones that did have.

Consistent with Bernhard and Campello (2007), Bartov, Givoly and Hayn (2002) claim that firms that meet or beat analysts' forecasts (previously referred as a positive surprise), report higher stock returns over the quarter compared to the ones that fail to meet their forecasts. Moreover, Bartov et al. (2002) add that such premium is possible to be achieved through earnings management and could be used as a strong indicator of future performance. Doyle, Lundholm and Soliman (2006) also document a price drifts after earnings announcement for firms that record a positive earnings surprise. Additionally, Doyle et al (2006) findings show that firms with large positive earnings surprise continue to outperform financially, institutional interest increases, transaction costs decrease and the underpricing is eliminated. Ke and Yu (2006) touch on a different aspect of financial analyst bias by suggesting that biased earnings forecasts are often issued to gain access to management and secure their jobs by providing more precise estimations yet making sure positive earnings surprises are achieved by the end of the period.

Clearly, a lot of effort was made in the past to understand the nature of analysts forecast error and whether this error is systematic or random. The behavioural side of the systematic bias in forecast revisions was covered by De Bondt and Thaler (1990) who report that earnings forecasts are too extreme to be rational and that analysts' forecast revisions show a trend of overreaction to previous information. A very important element in De Bondt and Thaler (1990) is the use of IBES estimates produced by Lynch, Jones & Ryan, member of the New York Stock Exchange which is also used by a lot of professional investors. This element, combined with their results of analysts' extreme optimism, allowed the authors to extrapolate the following: "there are many reasons to be sceptical that actual investors are subject to the same biases as student subjects in laboratory experiments" (De Bondt and Thaler (1990 p.52)), in referring to a result which had been reached initially by Kahneman and Tversky (1973) after experimenting on laboratory students related to the psychology of predictions. De Bondt and Thaler conclude that analysts are subject to overreaction and that behavioural explanations of anomalous trends should be taken seriously.

De Bondt and Thaler's conclusion is further confirmed by Hribar and McInnis (2012) who studies the association between analysts' earnings forecast and investor sentiment and their impact on stock returns. Hribar and McInnis (2012) argue that forecast error is positively significantly affecting stock returns and that the impact of sentiment index on cross-sectional return diminishes by 49% (for small versus large portfolios) when forecast error variable is introduced to the equation. Therefore, Hribar and McInnis (2012) indicates that "it appears that analyst forecast errors are significant intermediating variable in the cross-sectional patterns documented between sentiment and stock returns" (Hribar and McInnis (2012 p. 306)). Such relationship requires deeper review of the "investor sentiment" literature which is covered in the following section.

4.2.2. Market Sentiment

Sentiment surrounding the stock market is considered a very important factor in affecting investment decisions. As human beings, investors are subject to sentiment and it sometimes leads them to inappropriately translate given information. Sentiment is applied in various areas of finance literature and found to have various implications. For example, Daniel et al (1998) suggests that market price momentum is partially driven by sentiment such as investors overreact to private signals and underreact to public information. Similarly, Schmelling (2009) finds that sentiment is negatively related to future returns and mostly in the short and medium term horizons. Scheinkman and Xiong (2003) claims that investors' overconfidence plays a big role in bubble markets by stimulating prices volatility and trading volume, that is, by creating more speculative trading driven by heterogeneous beliefs. Consistently, Odean (1998) had found that overconfident traders trade more aggressively than rational ones and this is due to their superior self-belief in private information. As a result, trading volume and price volatility increase. According to the author, investors do not only overvalue their private information but they also misinterpret it. Bergman and Roychowdhury (2008) argue that firms even change their disclosure policies depending on the market sentiment level.

In short, behavioural market watchers seem to believe in the impact of market sentiment or at least the existence of one of its attributes. But what is exactly “sentiment”? According to Brown and Cliff (2004), “sentiment represents the expectations of market participants relative to a norm: a bullish (bearish) investor expects returns to be above (below) average, whatever average may be”. (Brown and Cliff (2004)). Baker and Wurgler (2006) also defines sentiment in the context of financial markets as the tendency to speculate, such that it drives the relative demand for speculative investments.

Investor’s sentiment is investigated by Neal and wheallley (1998) using three measures: Closed-end fund discount, ratio of sales to purchases and net mutual fund redemptions. Using data from 1933 until 1993, Neal and whealley (1998) report that fund discounts and net redemptions can predict the difference in returns between small and large firms but no significant relationship between sentiment and future earnings growth or inflation. Moreover, Brown and Cliff (2005) test the predictive power of sentiment on future stock returns. According to the authors, if sentiment levels push stock prices to higher levels surpassing the intrinsic values, stock returns of the following periods should be negative. Using a survey data to construct a sentiment index, their analysis show that market returns could be predicted over a period of 1 to 3 years using the sentiment index. It also confirms previous findings suggesting that future market returns are negatively associated with sentiment levels. In an attempt to explain the 1987 crash, Baur, Quintero and Stevens (1996) find no significant association between future returns and sentiment levels. Baur, Quintero and Stevens (1996) use closed-end-fund-discount as a sole proxy of sentiment index and concluded that either their variable is faulty or that sentiment levels preceding the crash had nothing to do with asset valuation during the crash event.

The relationship between investor sentiment and the cross-section of stock returns is further investigated by Baker and Wurgler (2006). In an indirect quantitative approach, the authors construct a sentiment index using principal component analysis based on six proxies: Closed end fund discount, return on IPOs, number of IPOs issued, turnover ratio, share of equity issued and dividend premium. Results from their analysis show a negative impact of investor sentiment over subsequent returns. In particular, when sentiment level is low, subsequent stock return appear to be high for small stocks, young stocks, non-dividend paying stocks, highly volatile and distressed stocks. Baker and Wurgler (2006) base their interpretation on the assumption proposed by Shleifer and Vishny (1997) and that is, since asset mispricing is a result of a demand shock, a shift in sentiment levels would mostly affect stocks that are more sensitive to speculative demand, harder to value, and stocks that are riskiest and costliest to arbitrage.

The choice of model to estimate investor sentiment has always been considered a dilemma to most of the academics. Attempts to estimate this behavioural issue varied between direct (survey primary data) and indirect (quantitative market proxies-secondary data). Brown and Cliff (2004) provide a comprehensive study about the different measures of investors sentiment. They found that both methods (direct and indirect) provide common features. However, they add that past returns are also a very important determinant of sentiment. Contrary to Baker and Wurgler (2006), Brown and Cliff (2004) results show that sentiment seems to be affecting large and institutional stocks rather than small and individual stocks.

Another popular proxy of investment sentiment is consumer confidence surveys. This variable is used by scholars to fit into different research questions. Bergman and Roychowdhury (2008) for example, use the Michigan Consumer Confidence Index to study how US firms change their disclosure policies depending on investor sentiment levels. They note that managers would try to maintain optimistic estimates about their company's performance over a long horizon. Consistently, their findings show that managers attempt to issue more voluntary management forecasts during low sentiment periods in order to "walk up" public expectations, but lower their forecasting activities in high sentiment periods. Likewise, Chen (2010) uses the same consumer index to demonstrate how a lack of market confidence could affect stock returns specially in bear periods such as 2008 financial crisis. After controlling for macroeconomic variables, Chen (2010) finds that the greater the market pessimism the higher the possibility of shifting from bull to bear market.

The use of consumer confidence by academics as a proxy of investor's sentiment is not only backed theoretical but also empirically. A closer look on how the state of consumer confidence could be related to investor's sentiment is discussed by Fisher and Statman (2003). Using Michigan Consumer Confidence index and the American Association of Individual Investors, the authors find a positive relationship between the change in individual investor's sentiment and change in consumer confidence. However, this isn't the case when institutional investors sample is used instead (Based on the Wall street strategists Survey). Fisher and Statman (2003) argue that this might be because Wall Street strategists understand well that the stock market is a leading indicator of the economy. Furthermore, they find a positive significant relationship between individual investor's confidence and returns on small stocks. In the same manner, Lemmon and Portniaguina (2006) find that the sentiment component of consumer confidence can forecast returns on stocks primary held by individuals. Nevertheless, they report that this behavioural result is not valid before 1977, arguing that "one possible explanation is that the dynamics of participation of households in the equity markets has changed over time" (Lemmon and Portniaguina (2006),p.1527). On an international scale, Schmeling (2009) finds that investor sentiment negatively predicts stock returns in 18 developed countries. Interestingly, Shmeling's results appear to be robust for value stocks, growth stocks, small stocks and for different forecast horizons. It is worth noting that Schmeling (2009) uses Consumer sentiment survey as a proxy of investor's sentiment since it is the most comparable proxy across countries because of the similarities in surveys conducted in different countries and its availability over different time horizons.

4.2.3. The Value Premium anomaly

The "value premium" is a well-documented phenomenon where stocks with high B/M ratios (Value Stocks) tend to earn higher returns than stocks with low B/M ratios (growth stocks). The reasons behind such anomaly is still an ongoing debate between finance scholars despite having a good deal of papers addressing this topic. In line with this debate, two theories were eventually born: the behavioural-based theory standing against the risk-based theory.

On the one hand, Risk-based explanations led by Fama and French (1992b and 1993) argue that higher return of value firms is a compensation for the risk held by the investor. Chen and Zhang (1998) also report that value firms are riskier since they have high financial leverage and face substantial uncertainty in their future earnings. On the other hand, Behavioural-based explanations, supported by De Bondt and Thaler (1987), Lakonishok shleifer and vishny (1994), Baker and Wurgler (2006) and many others, argue that naïve investors make their investment decisions based on past performances. Therefore, as naïve investors misprice stocks, they overvalue growth stocks and undervalue value stocks based on past performances.

Researchers took the matter a bit further by discussing the importance of market sentiment in explaining returns on value stocks and growth stocks. Baker and Wurgler (2006) for example denote that young, unprofitable and extreme growth stocks are harder to value and therefore are more affected by shifts in sentiment levels. Contrarily, Schmelling (2009) finds that the impact of sentiment on returns is significant for both value and growth firms but economically stronger for value firms than growth firms. The author denotes that sentiment negatively predicts stock returns, that is, when sentiment level increases, subsequent aggregate stock returns tend to decrease and vice versa. Besides, Schmelling adds that this impact is significant for countries that “are culturally more prone to herd-like investment behaviors as well as countries that have less efficient regulatory institutions” Schmelling (2009 p.406).

Investor sentiment and short term returns is also studied by Waggle and Agrrawal (2015) who used the percentage of “bullish” investors out of aggregate investors as a measure for market sentiment. For a sample of monthly stock returns between 1992 and 2010 and a monthly sentiment averages from the American Association of individual investors, Waggle and Wagrrawal (2015) show that sentiment is significantly negatively related to the following three and six months returns. Moreover, they report that this result is driven by growth firms rather than value firms, and holds for small, medium and big stocks. Contrary to previous suggestions, Lemmon and Portniaguina (2006) find no evidence in support of the relationship between sentiment and value premium. By using consumer confidence as a measure of investor sentiment, they find that returns on stocks with low institutional ownership are weaker than the ones with high institutional ownership. Their finding is consistent with the noise-trader hypothesis proposed by Lee, Shleifer and Thaler (1991) which argue that stocks that are dominantly held by individuals are more likely to be affected by sentiment shifts, which is also true to small versus big companies. Similarly, Ciner (2014) results prove that when sentiment index is high, aggregate stock returns are positive on the short run, but negative on the long run. This finding is only significant for small firms. Nevertheless, after using a frequency dependent regression framework, Ciner (2014) reports that stock market indexes and consumer confidence work in reverse causality.

4.3. Rationale and Research contributions: Analysts' forecast error and the value premium anomaly through market sentiment.

The combination of forecast error and market sentiment, and their impact on the value premium anomaly has never been studied before. While it is true that the literature surrounding market sentiment and stock returns has been well documented, there exists no previous study that considers the forecast error as a contributor of market sentiment, nor their relationship with the value premium anomaly.

The rationale behind this chapter is based on the belief that analysts' earnings forecasts should be considered an essential contributor of the market sentiment as they form significant expectation in the market surrounding the companies. At the same time, where it is true to some extent that earnings forecast error seems to affect stock returns, it cannot be this simple that investors blindly follow analysts' recommendation even after knowing the existence of such pattern. For example, how come investors who know already the significant repetitive optimistic forecasts and systematic downward forecast revisions found in many papers (Bernhard and Campello (2007), Bartov, Givoly and Hayn (2002), Yu and Ke (2006) and many more), yet still fall in the trap of earnings surprise and push prices upward. Therefore, this chapter proposes that the impact of forecast error on cross-sectional patterns of stock return cannot be observed directly, however, it would make more sense if forecast optimism was taken as a component of investor sentiment which in return might directly affect the cross-sectional return patterns such as value premium. This rationale is further supported by DeBondt and Thaler (1990) who state that overreaction is a pattern that can pervade even the most professional of predictions even though "market professionals are experts in their field and they have much at stake" (DeBondt and Thaler (1990 page 52)).

It is also strengthened by results shown in Hribar and McInnis (2012) who find that adding forecast error as an independent variable weakens the impact of sentiment on cross-sectional returns by 49% for small versus large firms. They also conclude that analyst forecast errors are significant intermediating variable in the cross section-patterns. The hypothesis in this research is drawn differently. Rather than taking forecast errors as an intermediating variable, investor sentiment index is calculated as a function of forecast error using the principal component analysis in order to capture the common component between forecast optimism and Baker and Wurgler (2006) sentiment variables. The value premium is then tested using the new sentiment proxy.

This chapter contributes to the literature in two ways. First, it proposes a new measure of investor sentiment index that embeds analysts forecast errors for all London Stock Exchange (LSE) companies from 1992 to 2015. This is motivated by the fact that the forecast error contributes to the overall market sentiment. Second, it addresses the relationship between investor sentiment, as a function of forecast error, and patterns in cross-sectional stock returns. The sentiment effect is distinguished relative to firm characteristics to examine whether it plays a part in exacerbating return anomalies, such as value premium.

In line of these contributions, the chapter attempts to answer the following research question: What is the impact of forecast error and market sentiment on the Value premium anomaly.

4.4. Methodology and sample selection:

4.4.1. Forecast error:

The first step in the analysis is to calculate analysts forecast error. For simplicity, the following equation is used:

a) $$FE_{hT} = \frac{F_{ht} - E_t}{|E_t|}$$

Where FE is average forecast error made in month h for year t, F ht is the EPS forecast in monthly horizon h for year ending t, Et is the actual EPS at year ending t. “h” is the monthly distance (11 to 1 horizon) from which the forecast was made until earnings announcement date. The forecast error is calculated monthly to fit into the time series analysis. For each month, forecast error is simply defined as the difference between monthly forecast and the yearly reported earnings per share, deflated by the reported earnings per share. This will produce a percentage of error made by forecasters when forecasting the end of year performance. It's important to remind about the purpose of this research which is to find how the aggregate forecast error made each month in LSE can contribute to the sentiment level, regardless whether this error is subject to biasness. Note that the denominator is kept in absolute value in order to save the sign of the nominator, which would tell whether the forecast is optimistic or pessimistic.

4.4.2. Investor Sentiment:

The next step is regarding investor sentiment index. There are number of different ways in which sentiment could be estimated.

The direct approach requires a survey analysis through which primary data are collected. This way consists of collecting data via questionnaires or interviewing individual investors then grading each answer to form a sentiment index. Glaser and Weber (2007) for example questioned around 3000 German online broker investors who had opened their online account prior to January 1997 and had at least one transaction from January 1997 until 2001. Their questions are designed to measure investor's overconfidence and come as follow:

- "What percentage of customers of your discount brokerage house have better skills (e.g. in the way they interpret information; general knowledge) than you at identifying stocks with above average performance in the future? (Please give a number between 0% and 100%)″
- "What percentage of customers of your discount brokerage house had higher returns than you in the four-year period from January 1997 to December 2000? (Please give a number between 0% and 100%)"

This research, however, follows an indirect approach in order to estimate investor sentiment index. There are many reasons why surveys are avoided in this analysis. First, the efficiency of data collected through surveys are usually hard to confirm specially when investigating behavioural aspects of individuals. A degree of suspicion will always be present because people may respond to surveys different to how they behave. Second, there exists one investor confidence survey collected by Lloyds Banking Group but available for a limited period. Since investor confidence surveys are rarely found, many studies used consumer confidence surveys to proxy for investor sentiment, and these are usually collected by governments or specialised research departments on monthly basis such as the University of Michigan in the US and the GFK consumer confidence index available internationally. Finally, and most importantly, the main aim is to observe the contribution of forecast optimism on investor sentiment, and this wouldn't have been possible if ready survey data are used. Therefore, an indirect approach is employed in an attempt to quantify sentiment levels using sentiment proxies. this approach consists of using secondary quantitative data of particular sentiment proxies. Prior work suggests a number of different proxies as stated in the previous sections. However, there is no definite answer to such behavioural estimation. This research follows a popular index proposed by Baker and Wurgler (2006) who use six proxies in order to estimate the investor sentiment index: closed-end fund discount, LSE share turnover, the total number of IPOs issued monthly, the monthly average of first day return on the IPOs, the share of equity issues in LSE, and dividend premium. Additionally, the analyst forecast error is added as the seventh proxy.

Closed-end fund discount (CEFD) is the average difference between net asset value (NAV) of closed-end fund stocks and their market prices. As opposed to open-ended fund, a closed end fund is a company that issues a fixed (closed-ended) number of stocks, then invests its capital in other projects. These stocks are then traded on stock exchanges. The fund is called at a discount (premium) when the market price of the stock is lower (higher) than the net asset value of the fund, which is the actual value of total investments. CEFD has a long history with market sentiment analysis. Many scholars including Lee et al. (1991) and Neal and Wheatley (1998) claim that CEFD is a proxy for sentiment. This is because when retail investors are bearish, fund discount increases. Therefore, CEFD is expected to hold a negative sign.

The Share Turnover (Turn) is the ratio of reported trading volume over the number of shares listed in LSE. This ratio performs as a liquidity measure. Liquidity is often seen as a sentiment indicator. Scheinkman and Xiong (2003) argues that "with short selling constraints, an asset buyer acquires an option to sell the asset to other agents when those agents have more optimistic beliefs. Agents pay prices that exceed their own valuation of future dividends because they believe that in the future they will find a buyer willing to pay even more". According to the authors, this gradually leads to bubble periods and larger trading volumes. Consequently, trading volume possesses a positive indication of investor sentiment. The sign of Turn is expected to be positive.

Initial Public Offerings IPOs also play an important role as a sentiment indicator. Demand on IPOs is believed to be very sensitive to sentiment state and this is reflected in first day return on IPO issues. Baker and Wurgler (2006) state that it is very hard not to involve investor's sentiment specially when first day returns on IPOs reach an extremely high figures. RIPO is included in this analysis as the average first day return on IPOs and is expected to be positively related to sentiment. Similarly, the number of IPOs issued in a month NIPO is another measure of sentiment. For a company to decide whether to go public or not is undoubtedly a very critical decision to make. Logically speaking, the period in which it decides to go public in is as crucial as the initial decision, such that, having an IPO in a high sentiment period differs significantly than having an IPO issued during low sentiment periods such as a financial crisis. Therefore, conceding that the number of IPOs are expected to be higher in high sentiment periods, NIPO is expected to be positively correlated with sentiment index. Another measure of investment sentiment is the share of Equity issues over total equity and debt issues (SE). This is the aggregate issues of equity financing and not just IPOs. Similar to IPOs, this measure is a sign of market strength and is expected to bear a positive sign.

The sixth proxy is dividend premium Divp, which is the difference in market to book ratio MTB between firms that pay dividend and those that don't. This proxy is believed to be inversely correlated to sentiment levels according to Baker and Wurgler (2007). In most cases, dividend paying stocks are based on a stable income stream transferring safety to investors. Baker and Wurgler (2006) argue that dividend payers are generally larger, more profitable but with lower growth opportunities. When MTB value of dividend payers is lower than MTB values of dividend non-payers, this is seen as a growth opportunity thus sentiment index is expected to be high in this case and vice versa. Given these characteristics, Divp is expected to be negatively correlated with sentiment index.

The last proxy of sentiment is FE (forecast error) which is the difference between average forecasted earnings per share EPS and actual reported earnings per share at the end of the year, divided by absolute value of reported earnings per share. Analysts forecasts are considered an important source of information and believed to affect investor's level of expectations about companies' performance. When the forecast is higher than the reported EPS the forecast is called optimistic and when it is lower it is called pessimistic.

Meanwhile, investor sentiment index is all about future expectations. In the immediate effect, forecast error is expected to share a positive relationship with sentiment index. This suggests that optimistic earnings forecast contributes to higher sentiment levels and pessimistic earnings forecast leads to lower sentiment levels.

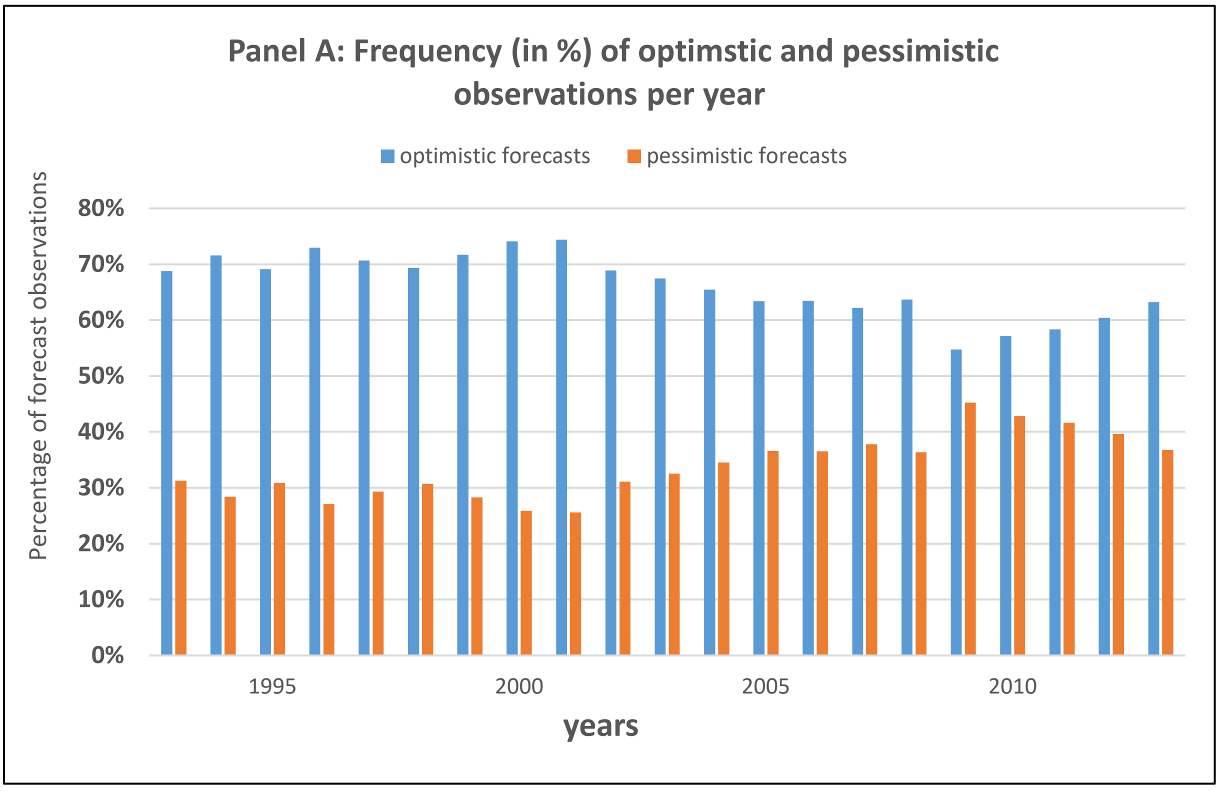
All public companies listed in London Stock Exchange were used as available from 1992 to 2013. Starting from 1992 was important to insure that analysts had adopted the third financial reporting standard (FRS3) in the UK. As stated in the previous chapter, the introduction of FRS3 has forced public companies to disclose more detailed information. It was clear that such introduction had an impact on financial analysts, specially when it comes to earnings per share forecasts (Acker, Horton and Tonks (2002)). Moreover, companies listed in LSE were collected as available in each year and this is important in order avoid the survivorship effect as each year the number of listed companies vary due to mergers, acquisitions, new entrants or companies leaving the index. At a particular month, companies followed by less than 3 forecasters were eliminated due to reliability issues and consistent with the literature.

As documented in Chapter 2, analysts' forecasts are proved to be optimistic to some extent and this is consistent with most of previous studies. An alternative illustration of this case is provided in Figure 4.1. This graph compares the yearly frequency (in percentage) of optimistic and pessimistic forecasts, where optimistic is the number of optimistic forecasts (Forecast error>0) per year divided by the total observations and pessimistic is the frequency of pessimistic forecasts (Forecast error<0) per year divided by the total observations. The bars clearly show the dominance of optimistic forecasts each year. The margin difference between optimistic and pessimistic forecasts reaches is peak in 2000-2001, which is due to the stock market bubble. However, pessimistic forecasts significantly increased as the financial crisis emerged in 2007-2008 then gradually recovered after 2009.

Figure 4.2 shows the yearly average percentage of forecast error made by consensus analysts. Results from this figure is consistent with Figure 4.1 regarding the dominance of optimistic forecasts. While Figure 4.1 shows that the number of analysts releasing optimistic forecasts is much higher than the number of times analysts are releasing pessimistic forecasts, figure 4.2 explains the sign each forecast is taking. The Moving Average Line shows that forecast errors are mostly positive meaning that analysts are overall optimistic. Again, the lowest optimism level is recorded in 2009 during the financial crisis, with the highest happened to be in 1993, 1994 and 2000.

Figure 4.1

Panel A shows the frequency in percentage of optimistic and pessimistic forecasts per year; where optimistic is the number optimistic forecasts (Forecast error>0) per year divided by the total observations, pessimistic is the number of pessimistic forecasts (Forecast error<0) per year divided by the total observations.



An explanation of all the proxies used in the principal component analysis is provided in table 4.1. The table also provides information for the control variables. Variables related to CEFD and NAV are collected using Thomson Reuters Datastream. Bloomberg Terminals database is used to get the IPO data as well as debt and equity issuances. Variables related to Divp including BTM and dividend payout ratios are available from Thomson Reuters Datastream. EPS forecasts data are downloaded from IBES which is available through Thomson Reuters Datastream. The control variables are collected from the UK office for national statistics and the UK General Affair of finance. They are used to control for macro-specific factors as will be discussed later.

Figure 4.2

Average of forecast error FE (in percentage) per year from 1993 until 2013. **[** $FE_T = \frac{F_t - E_t}{|E_t|}$ **]** ; F is the analyst forecast at time t, E is the reported earnings per share at time t.

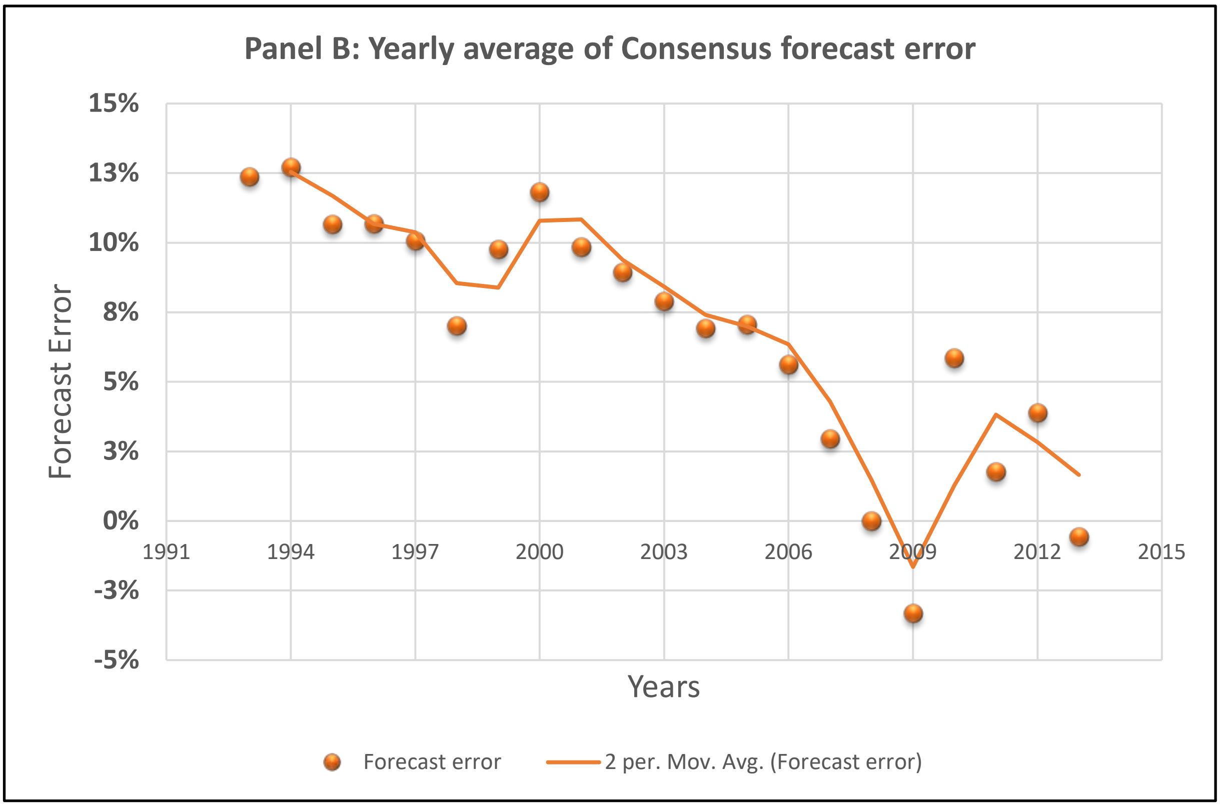


Table 4.1

Definitions, expectations and sources of variables used in the estimation of Sentiment as well as the control variables.

variable	explanation	Expected Sign	Source
CEFD	Value weighted average of Closed-End fund discount	negative	Datastream
Turn	Share turnover	positive	Datastream
Ripo	First day returns on IPO	positive	Bloomberg
Nipo	Number of IPOs	Positive	Bloomberg
Se	Share of equity issues in total equity and debt issues	Positive	Bloomberg
Divp	Dividend Premium: difference in market to book ratio between dividend payers and nonpayers	negative	EIKON Thomson Reuters
FE	Forecast error	positive	EIBES- Datastream
Control variables:			
Recession	a consecutive 2 quarters of negative growth in GDP		UK office for national statistics
Industrial production index	estimated index on industrial production levels		UK office for national statistics
Consumer Durable + nondurable	estimated index on durable + nondurable products level		UK office for national statistics
Consumer services	estimated index on consumer services level		UK office for national statistics
Consumer confidence index	Survey on consumer's confidence in the economy		EIKON Thomson Reuters-UK General Affair of finance
Business confidence index	Survey of manager's confidence in the economy		EIKON Thomson Reuters

The choice of time at which each proxy is expected to have an impact on investor's sentiment is another challenge since some variables might reflect a shift in sentiment earlier than others. Following Baker and Wurgler (2006), the first stage is to run the principal component analysis using each proxy and its lagged values and this results in a preliminary index with 14 loadings, one of each variable and its lagged proxy. After computing the correlation between the preliminary index and all 14 variables, the second stage consists of choosing the variables that are the most correlated with the index either lead or lagged, then run again the first principal component using the chosen variables. The seven proxies chosen are then standardised so that the index has unit variance.

b) $Sentiment_t = -0.2698\, CEFD_t + 0.4493\, TURN_{t-1} + 0.4439\, NIPO_t + 0.3986\, RIPO_{t-1} + 0.2419\, SE_t - 0.3125\, DIVP_{t-1} + 0.4617\, FE_{t-1}$

Equation b is the result of the second stage analysis. First thing to notice is that the sign of each loading appears as expected. Nevertheless, as the sample is withdrawn from a long period of time, it is a must to distinguish between business cycles and investor sentiment cycles. To do so, a third stage principal component analysis is run after controlling for macroeconomic factors. Therefore, each of the six chosen proxies is regressed on growth in consumer durables; consumer nondurables and consumer services; a dummy variable of recession (A consecutive 2 quarters of negative GDP); and growth in industrial production index. These macroeconomic variables are collected from the UK office for national statistics.

The residuals of each regression are then taken as the orthogonalised variables and used to run the first principal component.

c) $Sentiment_t = -0.2798\, CEFD_t + 0.4473\, TURN_t + 0.4422\, NIPO_t + 0.4042\, RIPO_{t-1} + 0.2423\, SE_t - 0.304\, DIVP_{t-1} + 0.4603\, FE_{t-1}$

Notice that the coefficient of each factor did not change much compared to the previous equation and the correlation between Sentiment index of equation c and b is 93%. More importantly, the first principal component captured 49% of the sample variance and only the first eigenvalue was above 1 meaning that the combination of these seven proxies mainly explains one factor which is the sentiment index.

Table 4.2

Summary statistics and correlations of sentiment index and sentiment components. Sentiment is the index estimated using the first principal component based on seven proxies: $CEFD_t$ is the monthly, value-weighted average discount on closed-end mutual funds. The second measure $TURN_t$ is the detrended natural log Turnover (5 years moving average) which is the ratio of reported trading volume over average shares listed in LSE. The third measure $NIPO_t$ is the monthly total number of initial public offerings issued in LSE. The fourth measure $RIPO_{t-1}$ is the average monthly first-day returns of initial public offerings, issued the previous month. The fifth measure SE_t is the share of monthly equity issuance to total equity and debt issuance. The sixth measure $DIVP_{t-1}$ is the lag of natural log of the value-weighted average ratio of market-to-book ratio of dividend payers to non-payers. The last proxy FEt_{-1} is the analyst forecast error as a ratio of the difference between earnings per share monthly forecast and end of year reported earnings per share, divided by end of year reported earnings per share. Each of the seven components are regressed against the growth in industrial production, the growth in durable, nondurable, and services consumption, and a dummy for recession (2 consecutive negative growth of GDP). The orthogonalised proxies are then used
in this analysis.

	Summary Statistics					Correlation matrix							
Variable	Obs	Mean	Std. Dev.	Min	Max	sentiment	CEFD	TURN	RIPO	NIPO	SE	DIVP	FE
$sentiment_t$	258	0.000	0.864	-3.356	2.417	1							
$CEFD_t$	288	-4.137	1.191	-27.544	30.321	-0.1679*	1						
$TURN_t$	288	7.063	3.862	2.709	41.182	0.6121**	-0.1367	1					
$RIPO_t$	288	4.066	23.975	-10.556	259.000	0.8041***	-0.0141	0.3911***	1				
$NIPO_{t-1}$	288	7.191	6.676	0.000	31.000	0.8257***	-0.0982	0.3513***	0.4165*	1			
SE_t	280	30.928	3.665	0.000	100.000	0.2467**	-0.184**	0.1276	0.2068**	0.032	1		
$DIVP_{t-1}$	288	-19.121	22.606	-1.016	0.473	-0.3184**	0.0812	-0.1312	-0.2321*	-0.1093	-0.201**	1	
FE_{t-1}	288	9.911	6.357	-3.451	35.553	0.4227***	-0.416**	0.3094***	0.1432	0.2451**	0.1334	-0.275*	1

***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4.2 above provides the descriptive statistics and correlation matrix of each component as well as the estimated sentiment. The first thing to notice in the correlation matrix is the low coefficient of CEFD (-16.7%) compared to previous studies such as Baker and Wurgler (2006) and Hribar and McInnis (2012)). This difference is normal since this study covers a more up to date sample and considering that open-ended funds became much more popular in recent years than closed-end fund (in the UK, open-ended funds occupy 69% of total mutual funds). Another interesting point is the high correlations between RIPO and sentiment (80.2%) and NIPO with Sentiment (82.5%). This is further illustrated in Figure 4.3 that clearly shows how the number of IPOs for example was seriously depending on the sentiment index. The year with the highest number of IPOs was 2000, during which it recorded the highest level of standardized sentiment as well at 1.61 on average. Similarly, 2009 recorded the lowest number of IPOs issued (total of 5) in a year where sentiment index was at the lowest figures (-1.47 on average). Another point to raise is the significant correlation between RIPO and NIPO (41.6%). Such correlation is expected since the more offerings listed in a year the more likely it is to increase the overall average of first day return. This correlation, however, does not harm the analysis as the variables will be used in a principal component analysis which seeks linear combination of variables such that the maximum variance is extracted, resulting in orthogonal uncorrelated factors.

Additional comparative figures between Sentiment index and the rest of the proxies are provided in the Appendices (Appendix 1 to 4).

As noted previously, it seems evident for many scholars that consumer confidence index is a powerful proxy for investor’s sentiment index (Bergman and Roychowdhury (2008), Chen (2010), Fisher and Statman (2003), Schmelling (2009)). Therefore, figure 4.4 compares the Sentiment index calculated in this study with consumer confidence survey conducted by the UK General Affair of Finance (accessed through Thomson Reuters Eikon).

The correlation between the two indices is 51%. The time series plot in figure 4.4 illustrates how both indices show signs of optimism during the internet bubble period (between 1995 and 2000), with another side of pessimism during the latest financial crisis between 2007 and 2012. Among the whole sample of study (290 months), there are 141 months of negative sentiment (Periods of optimism), 149 months of positive sentiment averages (periods of pessimism). If consumer confidence index was considered as the benchmark, there would be 175 pessimistic months against 115 optimistic ones.

Figure 4.3

Total number of IPOs issued yearly from 1992 until 2015, compared to the sentiment index SENT. Sentiment is the yearly average of monthly sentiment index estimated using the principal component analysis, based on seven sentiment components : Closed end fund discount, Forecast error, Number of IPOs, return on first day of IPOs, Turnover, Divident premium, percentage of equity issues over total equity and debt issues.

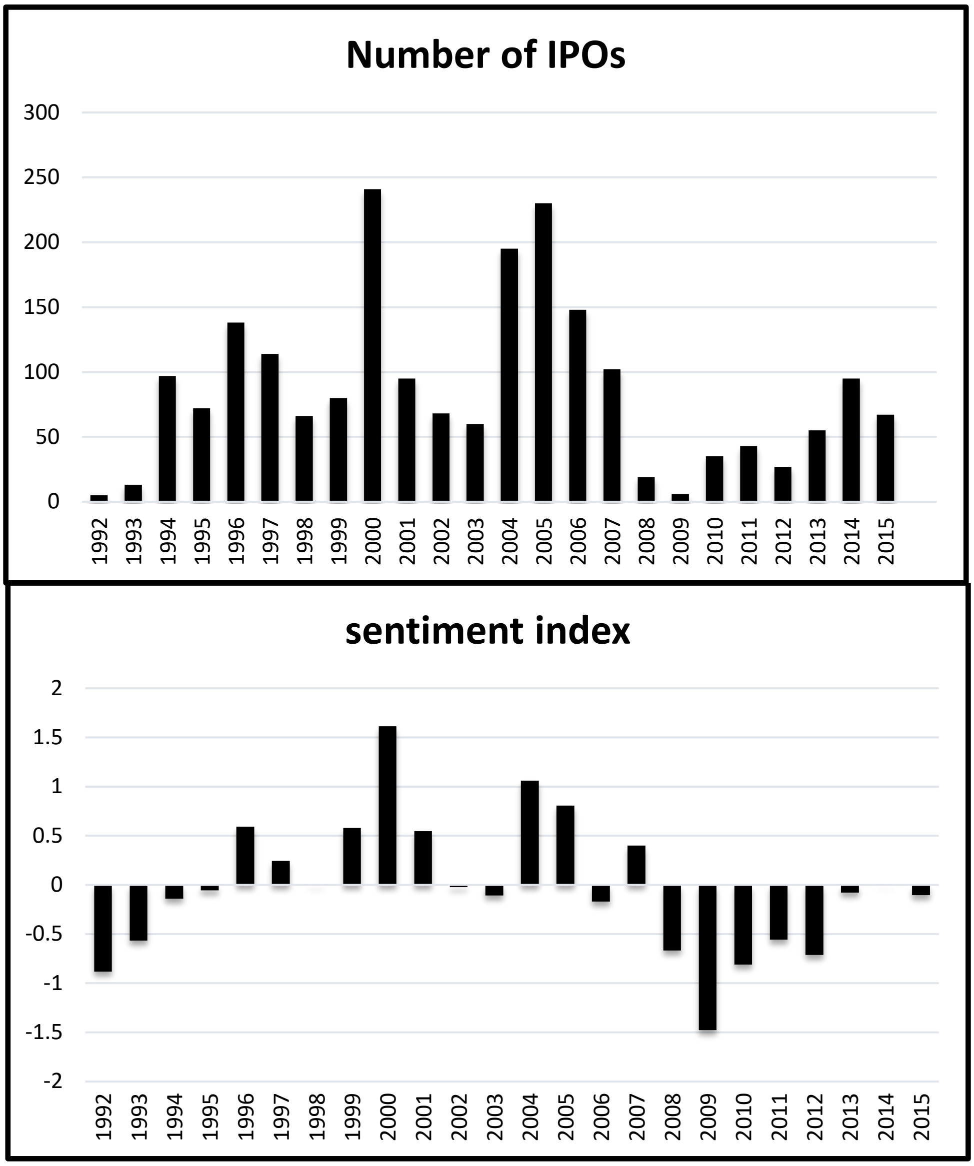
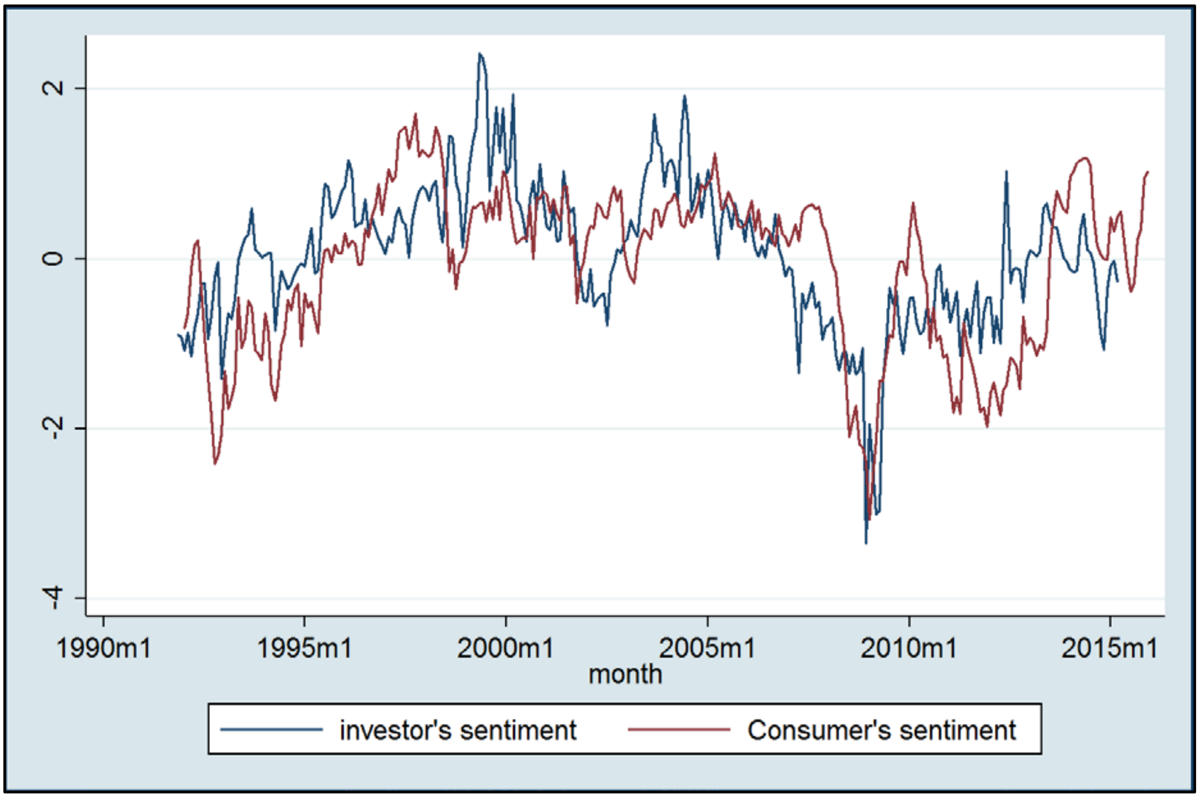


Figure 4.4
Time series plot of consumer confidence index and investor's sentiment index from 1992 until 2015 in the UK. Consumer confidence index is a survey data collected monthly by the UK General Affair of Finance (accessed through Thomson Reuters Datastream). Investor Sentiment is a monthly sentiment index estimated using the principal component analysis, based on seven sentiment components : Closed end fund discount, Forecast error, Number of IPOs, return on first day of IPOs, Turnover, Divident premium, percentage of equity issues over total equity and debt issues.



4.5. Empirical Tests and discussion:

The new index is believed to have an impact on stock returns and the value premium phenomenon in particular. In order to statistically test for such phenomenon, firms are sorted first depending on size, BTM (Book to Market ratio), profitability and investment aggressiveness, then compared during periods of different sentiment levels. For the BTM ratio, B is book value of equity at the end of fiscal year ending in year t-1 and M is market cap at the end of fiscal year t-1. Investment is the percentage change in total assets between the end of fiscal year t-1 and t-2. Profitability is the operating profitability divided by book equity. Size is the market cap at fiscal year end t. For each month, firms are sorted to 5 value-weighted portfolios of book-to-market quintiles, with low book-to-market firms which belong to the first quintile are called growth firms and value firms are the ones belonging to the fifth book-to-market quintile. The same sorting is applied using investment and profitability quintiles. Regarding size, firms are sorted into three different portfolios using 33% and 66% as breakpoints, as well as 5 portfolios of size quintiles. The Sentiment index follows a slightly different procedure where months are divided into low (months during which sentiment percentile is less or equal to 33%), and optimistic (months during which sentiment percentile is above or equal to 66%). Sentiment is called neutral if its percentile is between 33% and 66%.

Table 4.3

Average monthly percent of returns for portfolios formed on size and BTM ratio (Book to market), from January 1992 until December 1995 (288 months). Where B is book value of equity at the end of fiscal year ending in year t-1 and M is market cap at the end of fiscal year t-1. Stocks are sorted into five size groups (small to big) taking the market cap quintiles as breaking points. Stocks are also sorted according to the BTM quintiles from low to high. The combination of the two sorting produces 25 value weighted portfolios.

	Book-to-market quintiles						
Size quintiles	Low	2	3	4	high	HML	Average
small	-3.8610	-3.36626	-2.59356	-1.80512	-0.81516	3.04591	-2.48823
2	-1.6657	-1.48035	-0.73735	-0.29106	0.4823	2.14805	-0.73844
3	-0.0443	-0.02775	0.45653	0.56164	1.27611	1.32041	0.444446
4	0.62727	0.86072	1.08581	0.85486	1.64943	1.02216	1.015618
big	0.67046	0.74106	0.69115	0.84927	1.70973	1.03927	0.932334

Table 4.3 shows the percentage of stock returns on size and BTM portfolios using the quintile sorting for both variables (5 x 5). Consistent with the literature, the value premium can be clearly seen in this analysis as high BTM firms produce higher returns on average than low BTM firms. In every size row, most of stock returns gradually increases from low to high BTM but on a different rate or change. Fama and French (2015) find that the value premium is more evident in smaller firms. Results in table 4.3 also show a similar trend as smaller firms record higher differences in returns between firms with high and low BTM ratios. Moreover, HML monotonically decreases as firm size increases. For example, the average monthly return for big companies increases from 0.67% to 1.709% between growth and value companies respectively. Nonetheless, stocks that are extremely small (the first row) appear to have a very low return. Even more, the worst average return is recorded for the extremely small companies that have an extremely low BTM ratio (-3.861% monthly return).

Preliminary results regarding the impact of sentiment on stock returns could be seen in table 4.4. Returns in neutral periods are very hard to interpret as they they consist of mixed signs and no unique features. Consequently, the main focus in this research is on the extreme sides of Sentiment index which are low and high. Concerning size, panel A show that big companies outperform small ones during all sentiment periods. This difference, however, is slightly lower during high sentiment than low sentiment. By looking at each column separately, while small companies improve on average by 1.03% (between low and high sentiment levels), big companies improve by 0.34%. As a result, stock returns appear to be higher during high Sentiment periods for all firm sizes, but small companies are more prone to sentiment shifts than big ones. This is not consistent with Baker and Wurgler (2006) who report negative change of stock returns for small companies following an increase of sentiment level from low to high, but no impact whatsoever on big companies.

Panel B indicates how a shift in sentiment level can affect returns of growth and value firms. Despite an average return being higher in high sentiment compared to low sentiment, HML (High minus Low) seems to be stronger in low sentiment periods. By looking at the first column in panel B, growth firms have higher returns during high sentiment periods compared to low sentiment periods, with an average difference of 0.608% per month. Value firms, however, don't seem to be affected by the sentiment conditions as there was almost no difference between their average stock returns during high and low sentiment periods. The fact that returns on value firms remained unchanged between low and high sentiment levels followed by an increase in returns of growth firms during high sentiment levels, led HML to appear smaller in high sentiment periods. This result indicates that investors move away from growth stocks during low sentiment periods and if they are willing to invest at all, they would rather invest in value stocks. However, as the level of sentiment improves, the demand for growth stocks accelerates faster than the demand for value stocks, creating a bigger difference for growth stocks from low to high sentiment levels. The uncertainty surrounding growth stocks is a major factor in making this difference. This comes in line with the Baker and Wurgler (2006)'s theory stating that sentiment levels affect mostly stocks that are more sensitive to speculative demand and harder to value, however, the current result suggests that stock returns are positively affected by a positive shift in sentiment, which is the opposite of what is reported by Baker and Wurgler (2006). Baker and Wurgler (2006) compares portfolio returns with the last year-end sentiment level, and show that the long term stock returns are negatively correlated with sentiment levels (we reach similar results of the long term effect for small companies following the same approach, results are shown in appendix 7).

Table 4.4

Average monthly percent of returns for portfolios formed on Sentiment and BTM ratio (Book to market); Sentiment and investment; Sentiment and profitability, from January 1992 until December 1995 (288 months). Where B is book value of equity at the end of fiscal year ending in year t-1 and M is market cap at the end of fiscal year t-1. Investment is the percentage change in total assets between the end of fiscal year t-1 and t-2. Profitability is the operating profitability divided by book equity. Stocks are sorted according to the BTM quintiles from low to high. Months are sorted into three groups of sentiment (using 33% and 66% as the break-point percentiles). The combination of BTM and Sentiment groups produces 18 value weighted portfolios. The same thing applies to Investment with Sentiment, and Profitability with Sentiment. SMB is small minus big. HML is high minus low BTM. CMA is conservative minus aggressive investing. RMW is robust minus weak profitability.

Panel A: Size

Sentiment	small	2	3	4	big	SMB	average
low	-2.46338	-0.66039	0.49567	1.15282	1.07723	-3.54061	-0.07961
neutral	-2.71936	-1.34725	-0.01231	0.37549	0.29082	-3.01018	-0.682522
high	-1.42511	0.24133	0.89495	1.53112	1.41984	-2.84495	0.532426
Difference	1.03827	0.90172	0.39928	0.3783	0.34261		

Panel B: Book-to-market quintiles

Sentiment	Low	2	3	4	high	HML	average
low	0.59172	0.79329	0.81657	1.22577	2.16002	1.5683	1.117474
neutral	0.28357	0.24532	0.46127	-0.34028	0.6437	0.36013	0.258716
high	1.20036	1.50352	1.11016	1.74054	2.19409	0.99373	1.549734
Difference	0.60864	0.71023	0.29359	0.51477	0.03407		

Panel C: Investment quintiles

Sentiment	Conservative	2	3	4	Aggressive	CMA	average
low	0.8215	1.10511	0.83745	0.67244	1.84281	-1.02131	1.055862
neutral	0.2115	0.26301	-0.0649	-0.14191	0.08825	0.12325	0.07119
high	1.32989	1.28986	1.2771	0.989	1.12014	0.20975	1.201198
Difference	0.50839	0.18475	0.43965	0.31656	-0.72267		

Panel D: Profitability quintiles

Sentiment	weak	2	3	4	robust	RMW	average
low	-0.65238	1.08359	0.58851	1.18647	1.21728	1.86966	0.684694
neutral	-0.45799	-0.4738	-0.2353	0.10438	0.43305	0.89104	-0.125932
high	1.04171	0.20369	1.14792	1.20611	1.4304	0.38869	1.005966
Difference	1.69409	-0.8799	0.55941	0.01964	0.21312		

Results in table 4.4 of this study show the positive short term effect of sentiment levels on stock returns. More precisely, stock returns are higher when sentiment level of the same month (or the previous month at most) is high. The main argument in this analysis is that reaction of stock prices can hardly be attributed to sentiment levels of the previous year, in the sense that a fast integrated markets reflect the sentiment proxies very quickly.

Additionally, the use of forecast error as a seventh proxy of sentiment is believed to have contributed to this impact.

Panel C of the same table provides a different pattern that is regarding the investment ratio. Investment quintile is a measure of investment aggressiveness having 1 (conservative investing) and 5 (aggressive investing). Firms having a conservative month of investment appear to have lower returns, only in low sentiment. During high sentiment, firms that are investing aggressively have a slightly lower returns than conservative firms with a monthly difference CMA of 0.209% (conservative minus aggressive). Consistent with Lakonishok shleifer and vishny (1994). the theory of overreacting and herding could be clearly seen in this panel. The fact that aggressive firms earn more during low sentiment might be a sign of strength specially during a period of general pessimism, resulting in an overreaction to this sign.

Panel D presents figures concerning the return on profitable companies during different sentiment levels. In this panel, profitable firms barely improve their monthly return when sentiment shifts from low to high. Contrarily, returns on firms with weak operating profitability jumps significantly from -0.652% to 1.04171% after sentiment index improved from low to high. As a result, RMW (robust minus weak) drops from 1.87% to 0.388%.

This finding supports the theory that unprofitable firms are harder to value and tend to be more affected by Sentiment. Results in chapter 4 also confirm this suggestion as forecast error was found to be negatively correlated with firms' performance, meaning that forecast error is higher when firms reporting losses, decrease in their earnings, or firms that did not distribute dividends.

Equation d examines the robustness of the effect of sentiment on value premium, where excess returns are used as a dependant variable and the regression is run for value firms and growth firms separately in order to compare the coefficients of each panel apart.

$$d)\ r_{it} - r_{ft} = \alpha_t + \beta_1 SENTIMENT_t + \beta_2 MP_t + \beta_3 SMB_t + \beta_4 RMW_t + \beta_4 CMA_t + \varepsilon_t$$

where r_{it} is the return on portfolio of growth stocks or value stocks, Sentiment is the sentiment index; MP is the market premium (market return minus risk free rate); SMB is return on small minus big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term.

Table 4.5

Regression analysis of excess returns on Sentiment index, and Fama and French (2015) factors using OLS and Newey-west robust standard errors. Where excess return is return on portfolio of growth or value stocks minus risk free rate (one month treasury bill), Sentiment is the sentiment index; MP is the market premium (market return minus risk free rate); SMB is return on small minus return on big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term.

Panel A: OLS

Excess	Growth		Value	
Return	coef	se	coef	se
Sentiment	0.228***	(0.0394)	0.145***	(0.0338)
MP	0.827***	(0.0426)	0.833***	(0.0365)
SMB	-0.0987**	(0.0430)	-0.186***	(0.0369)
RMW	-0.00461	(0.0394)	-0.0850*	(0.0338)
CMA	-0.00553	(0.0376)	0.0738*	(0.032)
Constant	-0.0788**	(0.0371)	-0.0732	(0.0318)
R-squared	0.655		0.596	

Panel B: Robust SE/Newey-West

Excess	Growth		Value	
Return	coef	se	coef	se
Sentiment	0.228***	(0.0525)	0.145***	(0.0435)
MP	0.827***	(0.0641)	0.833***	(0.0507)
SMB	-0.0987	(0.0670)	-0.186***	(0.0419)
RMW	-0.00461	(0.0623)	-0.0850*	(0.0438)
CMA	-0.00553	(0.0517)	0.0738*	(0.0434)
Constant	-0.0788	(0.0771)	-0.0732	(0.0642)

se: standard errors

*** p<0.01, ** p<0.05, * p<0.1

Using Newey-West regression is essential in order to control for the serial correlation present in the sample. Coefficients, raw standard errors and robust standard errors can be seen in table 4.5 above. Panel A represents the OLS regressions where coefficients of growth and value firms' samples can be seen. Panel B shows the same coefficients, but with Newey-west robust standard errors. In all regressions, MP, SMB, RMW and CMA are used as control variables following Fama and French (2015).

Interestingly, Sentiment coefficient in the growth panel is greater than the sentiment coefficient in the value panel. The slope of the relationship between sentiment and excess returns on growth stocks is 0.228 compared to 0.145 for value stocks. Both coefficients being statistically significant at 1% confidence level, this finding supports the hypothesis that growth firms are more sensitive to sentiment than value firms, which is reflected in stock returns as a result. It is important to note again that the impact of sentiment index on stock return is a short term one since this index consists of two proxies set at time t, and another four components that are lagged to one-month (FE, Turn, RIPO and DivP). Taking for example the coefficient of RIPO, combining figures from equation c and table 4.5 allow us to say that the average monthly return on IPOs affected positively subsequent monthly stock returns of companies in LSE. This short term impact of RIPO was also evident in forecast error FE. Since sentiment index affects positively stock returns; and since sentiment index is positively significantly correlated with forecast error (lagged to one month), an increase in forecast error is likely to lead to an increase in excess returns. In other words, excess returns are more likely to be positive following a month of optimistic consensus forecasts.

In table 4.6 below a separate regression of excess return is run for each BTM quintile. This gives more detailed coefficients about the role of Sentiment in each panel of companies. Consistent with previous results, excess returns of Panel 1 appear to be the most affected by Sentiment index with a coefficient of 0.228 significant at 1% level. Sentiment coefficient decreases almost monotonically when BTM increases from quintile 1 to quintile 5. Moreover, one can also induce that a shift in forecast error have a higher impact on growth firms than value firms. A possible reason is that growth firms are harder to predict and followed by less analysts than value firms, which is consistent with the theory that growth firms are harder to value.

Table 4.6

Regression analysis of excess return on Sentiment index, and Fama and French (2015) factors Newey-west robust standard errors. Data was divided into five BTM panels from 1 to 5 (low to high). Where excess return is return on portfolio of growth or value stocks minus risk free rate (one month treasury bill), Sentiment is the sentiment index; MP is the market premium (market return minus risk free rate); SMB is return on small minus big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term.

Newey-West Regression					
Excess Return	BTM Quintiles				
	1	2	3	4	5
Sentiment	0.228***	0.223***	0.228***	0.163***	0.145***
	(0.0525)	(0.0441)	(0.0420)	(0.0501)	(0.0435)
MP	0.827***	0.839***	0.830***	0.778***	0.833***
	(0.0641)	(0.0633)	(0.0603)	(0.0795)	(0.0507)
SMB	-0.0987	-0.165***	-0.114***	-0.0632	-0.186***
	(0.0670)	(0.0405)	(0.0436)	(0.0557)	(0.0419)
RMW	-0.00461	0.00757	-0.185***	-0.126***	-0.0850*
	(0.0623)	(0.0593)	(0.0495)	(0.0463)	(0.0438)
CMA	-0.00553	-0.0691	0.0901*	0.0526	0.0738*
	(0.0517)	(0.0499)	(0.0501)	(0.0491)	(0.0434)
Constant	-0.0788	-0.0650	-0.0914	-0.0820	-0.0732
	(0.0771)	(0.0687)	(0.0652)	(0.0679)	(0.0642)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Results in this study adds to findings of some previous studies but contradicts with others. Few articles such as Baker and Wurgler (2006, 2007), support the idea that sentiment index affects negatively future stock returns (in the long run), this study finds that sentiment affects positively stock returns (in the short run) on a monthly basis. Overall, it is consistent with Ciner (2014) who states that sentiment affects positively stock returns in the short term and negatively in the long term but only for small firms.

In addition, this study shows that this pattern is significant in the UK for growth and value firms, but stronger for growth and small firms. However, it contradicts results in Brown and Cliff (2004) who document that sentiment affects returns on large and institutionally owned companies. It is also inconsistent with Schmelling (2009) who report that sentiment impact is qualitatively more powerful on value firms than growth firms.

Furthermore, this study doesn't agree with McInnis and Hribar (2012) regarding the use of forecast error as an intermediary between sentiment and stock returns. As a reminder, McInnis and Hribar (2012) report a positive relationship between forecast error and stock returns and claim that forecast error is an intermediary of sentiment as it absorbs most of the impact power shown by sentiment alone on stock returns. One possible reasons could be the common component shared between sentiment index and forecast error, resulting in forecast error being collinear with sentiment index. In fact, this particular point is addressed by the present research as the correlation between forecast error and sentiment index proved to be significant and equal to 42.2%. Based on this argument, this study shows how sentiment index, as a function of forecast error and other traditional components, has a powerful impact on stock return without one replacing the other.

4.6. Sensitivity analysis:

4.6.1. Re-estimating Sentiment index without Forecast Error:

As a robustness check, the sentiment index is re-estimated this time after excluding Forecast error. This extra step is essential to the analysis for three different reasons. First, it will allow us to see whether forecast error has really contributed to the sentiment index or not. Second, it will explain whether the significant results related to stock returns were mainly driven by the inclusion of forecast error in the sentiment index or simply by the other variables. Third, it will enable us to properly compare results with other studies.

The following equation is obtained after running the principal component analysis based on six proxies:

e) $$Sentiment^{*}{}_{t} = -\,0.2003\,CEFD_t + 0.4968\,TURN_{t-1} + 0.5419\,NIPO_t + 0.468\,RIPO_{t-1} + 0.2863\,SE_t - 0.3441\,DIVP_{t-1}$$

Sentiment* is the new index estimated without including forecast error. Where all variables are as explained earlier, the sign of each coefficient remains unchanged. However, the exclusion of forecast error affected the coefficients themselves (in absolute value), with the biggest change occurring for the coefficients of NIPO (+0.0997) and

CEFD (+0.0795). Nevertheless, the first principal component of equation e captured only 33.4% of the sample variance compared to 49% when Forecast error was included (equation c). Furthermore, the correlation between Sentiment* and the consumer confidence index is 0.47 compared to 0.51 with Sentiment.

In order to see the impact of Sentiment* on excess return and value premium, Newey west regression is run again as seen in the following equation:

$$f)\; r_{it} - r_{ft} = \alpha_t + \beta_1 Sentiment_t^* + \beta_2 MP_t + \beta_3 SMB_t + \beta_4 RMW_t + \beta_4 CMA_t + \varepsilon_t$$

Where Sentiment* is the sentiment index obtained from the principal component analysis based on six proxies (excluding forecast error), the rest of the variables are the same as explained in equation d. Results of regression e are presented in table 4.7.

Table 4.7

Regression analysis of excess returns on Sentiment* index, and Fama and French (2015) factors using Newey-west robust standard errors. Where excess return is return on portfolio of growth or value stocks minus risk free rate (one month treasury bill), Sentiment* is the sentiment index without the forecast error; MP is the market premium (market return minus risk free rate); SMB is return on small minus return on big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term.

Robust SE- Newey West of Sentiment*

	Growth		**Value**	
Excess Return	**coef**	**se**	**coef**	**se**
Sentiment*	0.1827***	0.0495	0.166***	0.0442
MR-RF	0.7968***	0.0599	0.7608***	0.0699
SMB	-0.1134*	0.068	-0.0717	0.0526
RMW	-0.0143	0.0576	-0.1288***	0.0465
CMA	-0.006	0.0524	0.0503	0.0506
Constant	-0.0728	0.078	-0.0794	0.0671

se: standard errors

*** p<0.01, ** p<0.05, * p<0.1

The coefficient of Sentiment* remained positively significant meaning that Sentiment* index has a positive impact on Excess return even after excluding the forecast error. However, excess returns of growth stocks appear to be affected more by Sentiment rather than Sentiment*. This is reflected in a decrease of the coefficient from 0.228 (for Sentiment) to 0.1827 (for Sentiment*). Both figures are significant at 1% confidence level. Where the only change made between both was the exclusion of forecast error, such result implies that forecast error is significantly affecting excess returns on growth stocks. When Forecast error is invited to the equation, the coefficient appears to be higher. Excess returns on value stocks, however, remain unaffected by the change.

To check in details whether this difference is statistically significant or not, regression g estimates the impact made by the difference between Sentiment and Sentiment* on excess returns of growth and value stocks. This difference is meant to represent the inclusion of forecast error.

$$g) r_{it} - r_{ft} = \alpha_t + \beta_1 Difference + \beta_2 MP_t + \beta_3 SMB_t + \beta_4 RMW_t + \beta_4 CMA_t + \varepsilon_t$$

Everything else remains as explained earlier, Difference is the difference between Sentiment and Sentiment*. Table 4.8 shows a positive coefficient significant at 1% for growth companies only (BTM quintile equal to 1). This significant difference implies that the introduction of forecast error to the Sentiment showed a significant positive impact on stock returns but only growth companies' stock returns. The coefficient of Difference could not be found significant on the rest of the BTM quintiles.

4.6.2. Sensitivity analysis: Re-estimating the relationship between the long-term stock return and sentiment levels.

As stated earlier, Baker and Wurgler (2006), Brown and Cliff (2005), Ciner (2014) and others claim that stock returns are affected by the sentiment levels in the long term. As a robustness check and to allow for comparison, the same was re-estimated in this research using the sentiment index lagged by one year. Results in appendix 5 show a very minimal change in stock returns for growth stocks when the sentiment level increases from low to high (with an increase of 0.17% on a monthly average). Similarly, the change in returns of small companies was even smaller with a decrease of -0.05% on a monthly average when sentiment increases from low to high. The magnitude of change in stock returns of big and value companies was higher than small and growth companies.

This finding contradicts with the claim that the sentiment changes affect stock returns on the long term. However, it supports the main argument in this analysis that the reaction of stock prices can hardly be attributed to sentiment levels of the previous year, in the sense that a fast integrated markets reflect the sentiment proxies very quickly. Additionally, the use of forecast error as a seventh proxy of sentiment is believed to have contributed to this impact.

Table 4.8

Regression analysis of excess returns on Difference, and Fama and French (2015) factors using Newey-west robust standard errors. Where excess return is return on portfolio of growth or value stocks minus risk free rate (one month treasury bill), Difference is the difference between Sentiment and Sentiment*. MP is the market premium (market return minus risk free rate); SMB is return on small minus return on big companies; RMW is return on robust companies (companies with high operating profitability) minus return on weak companies (firms with low operating profitability); CMA is return on conservative (companies with low investment rates) minus return on aggressive companies (firms with high investment rates); ε_t is the residual term.

Newey West Regression					
Excess	BTM Quintiles				
Return	**1**	**2**	**3**	**4**	**5**
Difference	0.1002***	0.063	0.0505	0.0478	0.0036
	0.0349	0.042	0.037	0.0298	0.0389
MR-RF	0.7822***	0.77***	0.7803***	0.7984***	0.7267***
	0.0670	0.0706	0.0683	0.0525	0.0603
SMB	-0.134***	-0.123*	-0.190***	-0.201***	-0.0861*
	0.0460	0.0703	0.042	0.0394	0.0492
RMW	-0.226***	-0.0477	-0.03	-0.1120**	-0.158***
	0.0526	0.0635	0.0579	0.0440	0.050
CMA	0.1103**	0.0135	-0.0507	0.0861*	0.0650
	0.0539	0.0558	0.0493	0.0463	0.0527
Constant	-0.070	-0.0577	-0.0442	-0.0600	-0.0661
	0.0771	0.0855	0.0778	0.0682	0.0705

se: standard errors

*** p<0.01, ** p<0.05, * p<0.1

4.2. Conclusion:

In this study, the relationships between sentiment, analyst forecast error and stock returns are examined. Previous studies concerning the impact of market sentiment do not consider the role of analysts' forecasts. This research contributes to the literature by taking into consideration the forecast error as a major component of investor sentiment, motivated by its importance in setting the market expectation in the stock market, and investigates its effect on the short term stock returns and the value premium anomaly.

Accordingly, the sentiment index is estimated using principal component analysis based on six market proxies following Baker and Wurgler (2006) and including the forecast error as the seventh proxy. All companies in London Stock exchange are investigated from January 1992 until December 2015. The first stage analysis show that sentiment index is positively significantly correlated with forecast error, that is, when monthly aggregate earnings forecast is optimistic, investor sentiment tends to be high in the following month and vice versa.

More interestingly, sentiment index proves to be positively related with stock returns meaning that stock returns increase when sentiment index is higher. While big and value companies appear to have larger returns in general, small and growth companies seem to be more prone to sentiment shifts than big ones. When the sentiment level shifts from low to high, stock returns of growth companies appear to increase significantly. Furthermore, firms having a conservative month of investment appear to have lower returns, only in low sentiment periods. During high sentiment, however, firms that are investing aggressively tend to have lower returns than conservative firms. Even more, stocks with high operating profitability barely improve their monthly return when sentiment increases from low to high. These findings are inconsistent with Baker and Wurgler (2006) and Brown and Cliff (2005) who find that the sentiment index negatively affects stock returns on the long run.

Having a significant positive correlation between forecast error and sentiment index, it becomes possible to interpolate that stock returns and forecast error share a positive relationship as well, such that, stock returns increases when earnings forecasts are more optimistic.

To conclude, this research provides a different dimension of the role of analyst forecast error in stock markets. Even more, it doesn't support the idea that earnings forecast affects directly stock returns, instead, it offers a valid argument that aggregate sentiment should be looked at as a function of forecast error which in return affects short term stock returns.

Chapter 5:

Conclusion

Financial analysts are considered essential to the existence of the financial markets and the global economy. Their intermediate role consists of feeding the market with analysis, reports, forecasts and investment recommendations. As a result, the market digest what they release of information which reflects to some extent companies' performances based on fundamental analysis. Therefore, the accuracy and reliability of the figures generated by analysts might have serious implications on the stock market.

Motivated by the importance of financial analysts' forecasts in the stock market, this research provides an all around investigation of the nature, causes and consequences of analysts' forecasting errors made by financial analysts targeting companies listed on London Stock Exchange. There are three empirical studies provided in this research and addressing every issue surrounding analysts' forecasts separately, but offered in an order that follows a logical reasoning in order to fulfil the aim of the research. The first empirical study aims to build a better understanding about financial analyst forecasts, their accuracy and rationality. While doing so, it highlights few weaknesses found in data sampling provided in previous studies. One of these drawbacks is setting the fiscal year-end date as the ending of the forecast period, whereas analysts keep forecasting until the announcement date which is usually between 1 to four months after the fiscal year end. Another drawback is including a sample data of firms that have their fiscal year ending in December only. Such weaknesses are believed to be misrepresenting the relevant aggregate error made by financial analysts' forecasts. Using 21 years of monthly consensus forecasts data, analyst forecasts are proved to be generally optimistic. This is evident when comparing the forecasts made by analysts to the reported earnings per share released by the company at the end of the fiscal year. Findings show that analysts forecasts are optimistic, but not as optimistic as the literature suggests. Further robustness analysis confirms this disparity when applying the closing year end as the last forecasting date as well as December year only firms.

Moreover, despite that preliminary results show that forecast error decreases as it approaches the end of the year, this downward trend could not be proven statistically. This trend is a well-documented phenomenon in the literature (Debondt and Thaler (1990), Capstaff et. al (1995) and Capstaff et. al (2001)). Moreover, the last forecast in the year seems to stay above the realised earnings. Such result defies that managers try to walk down the analysts' forecasts in order to create a positive surprise after the announcement date. Contrary to previous studies such as Easterwood and Nutt (1999), this study couldn't find any evidence about the relationship between forecast error and previous years' earnings. This implies that previous year's earnings do not lead to an overreaction of related future forecasts and that analysts are not proved to be irrational.

The second empirical study argues that analysts' forecast error may be misled by external forces that are hard to observe, in particular earnings management. Managers use earnings management as a tool in order to make short term adjustments to their company's earnings, by using accruals management or direct changes in real activities expenditures (real earnings management). There are many motives as to why managers may seek such methods. They may manage earnings downwards or upwards to smooth out earnings over a set of fiscal periods. Another reason could be to boost earnings so avoid reporting losses.

Following the Modified Jones model introduced by Dechow et al. (1995) to estimate accruals-based earnings management, and Roychowdhury (2006) to estimate real earnings management, the second chapter examines the same sample used in chapter 2 over a period from 1993 to 2013. Additionally, chapter 3 controls for a possible endogeneity using Generalised Methods of Moments. This is mainly due to a likely reversal causality between analysts' forecasts and and earnings that are managed in order to meet or beat the forecast. Moreover, a sample of suspicious firms is filtered to further control for this problem. Nevertheless, robustness tests show that managers rely on earnings management mainly to avoid losses rather than meeting or beating analysts' forecasts.

Findings show that earnings management affects positively forecast error. This means that as managers manage earnings, analysts do not seem to anticipate these changes thus the error appears to be increasing. However, this is statistically significant only for accruals-based management and not real earnings management. A possible explanation for this difference is the timing in which both adjustments are done. While accruals earnings management are often done by the end of the fiscal year to get a better picture of what is expected, adjusting real operational activities require an interference during the fiscal year which gives an time advantage for analysts to capture and reflect the changes in their analysis.

The third empirical chapter attempts to examine the consequence of analyst forecast errors, specifically its impact on the value premium anomaly through market sentiment. This is achieved by using investor sentiment index as an intermediate variable. The main rational of chapter 4 lies in the definition of investor sentiment as the market expectation towards a norm. As the same applies to earnings forecasts, a common component could be observed between forecast optimism and investor sentiment level. Consequently, the analysis in this chapter introduces a new index of investor sentiment using a principal component analysis based on seven proxies of investor sentiment, one of which is Forecast Error.

The sample in this chapter is expanded to all companies listed in London Stock Exchange and to a period starting from 1992 until 2015. This is essential to gather enough data required to conduct the statistical analysis. Results show a positive correlation between investor sentiment and forecast error. This indicates that when analysts' forecasts are optimistic, investor sentiment is more likely to be high. Moreover, the chapter tries to explain the popular value premium phenomenon based on investor sentiment and forecast error. Consistent with Fama and French (2014), results show that value firms beat growth firms in general. However, the value premium seems to be decreasing when sentiment level increases from low to high. This is true because growth firms appear to be more sensitive to shifts in sentiment levels than value firms. Moreover, sensitivity analysis show that sentiment shifts do not affect stock returns on the long run, which is inconsistent with previous studies (Baker and Wurgler (2006), Ciner (2014), among others). A possible explanation is that the reaction of stock prices can hardly be linked to sentiment levels of the previous year, in the sense that a fast integrated markets reflect the sentiment proxies very quickly. The contribution made in the third empirical chapter consists of showing the impact of forecast error on short term stock returns, by proposing a different behavioural dimension based on investor sentiment. Therefore, it offers a valid argument that aggregate sentiment should be looked at as a function of forecast optimism due to the common components they share.

Despite all the effort put to conduct a robust research project, this study is still subject to many pitfalls that can be addressed in future studies. First, the data used in this research is based on consensus forecasts that are gathered on a monthly basis which helps to gain a broad picture of the nature of these forecasts together. Nevertheless, further analysis regarding the individual characteristics of analysts can better address the issues surrounding the performance and rationality of financial analysts. The cross sectional features of analysts such as their ranking, size of the company they belong to, their experience, level of education and others, can explain a lot of the patterns that were discussed earlier. Second, the model of estimation of earnings management proposed first by Jones (1991) and later adjusted by Dechow, Sloan and Sweeney (1995) faces a lot of criticism by academic accountants as to how effective this could be in detecting earnings management, especially that this model might capture other shifts in discretionary accounts that are not mainly done under the objective of managing earnings. While this could be true to some extent, the research can be improved by applying and comparing different models that are capable of capturing earnings models such as “Benford’s law”. Third, the sentiment index is estimated based on 7 variables that are believed to be the best proxies of investor’s sentiment in the market. Nevertheless, this is considered a limitation as it’s an indirect way in estimating the investor’s sentiment by capturing the variability of its proxies. A further improvement would be to conduct a survey analysis targeting financial market practitioners, managers and investors in order to directly estimate the market sentiment. The American Association of Individual Investors AAII in the United States collect similar surveys on a monthly basis, however, there exists no similar repetitive surveys in the UK. Such approach is time consuming and costly thus restricted this research to stick with a rather indirect method.

To conclude, the combination of all empirical studies offers an all around investigation of the areas surrounding analysts’ forecasts. While it contributes to the field of finance by pointing out at weaknesses and shortcomings that could be exploited among market participants, it opens the door for other research studies in finance and other social science disciplines to further investigate and improve the efficiency of the financial markets.

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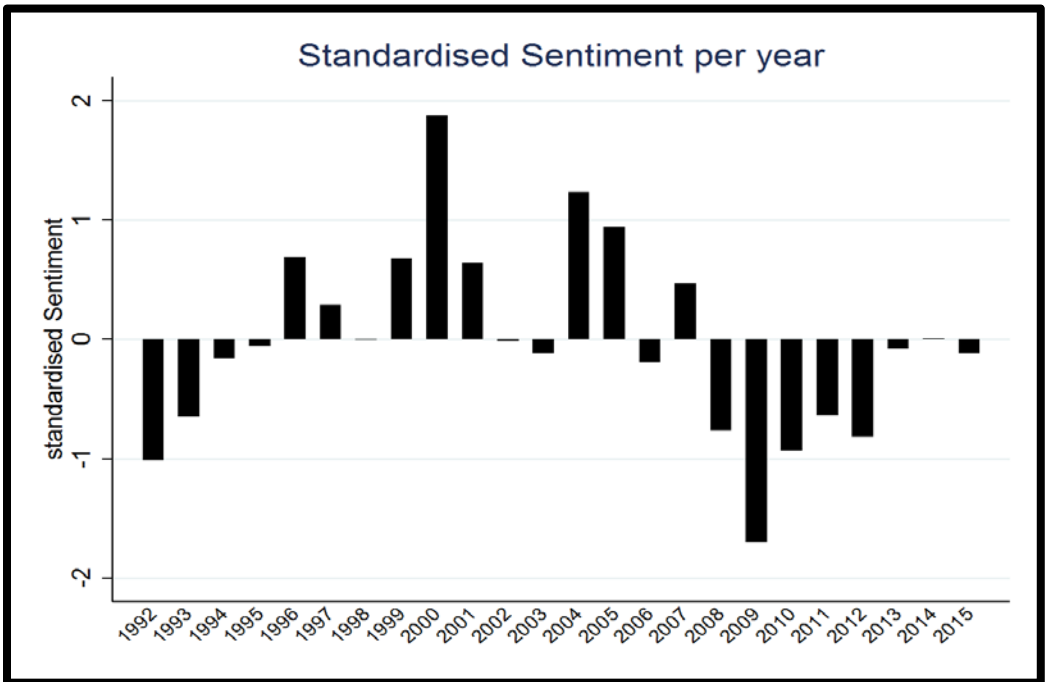
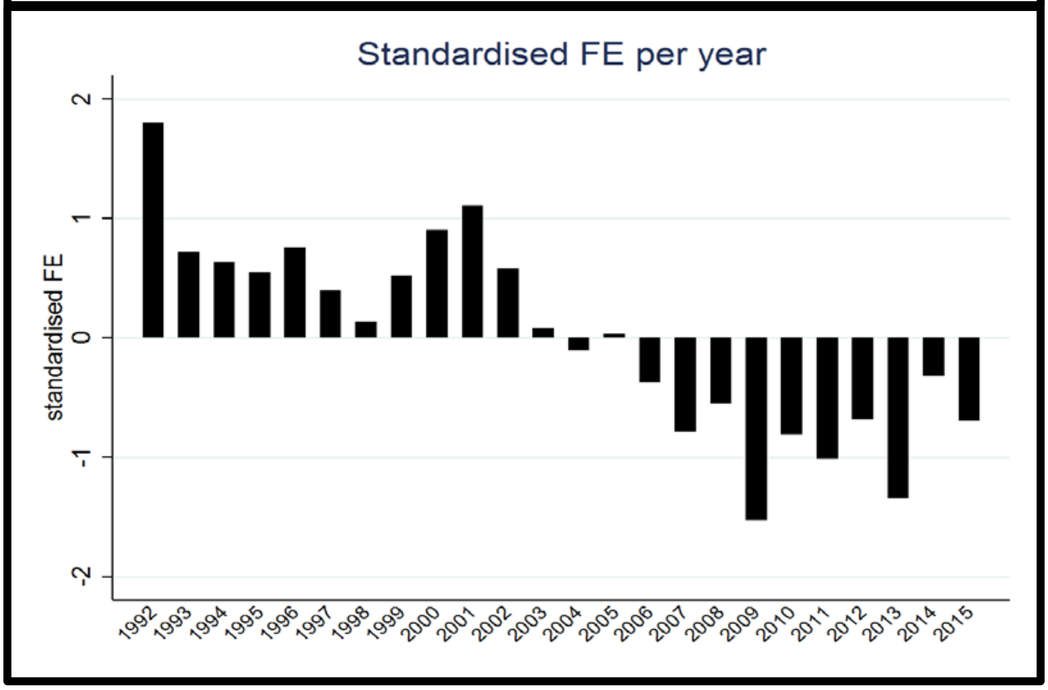
Appendix 1

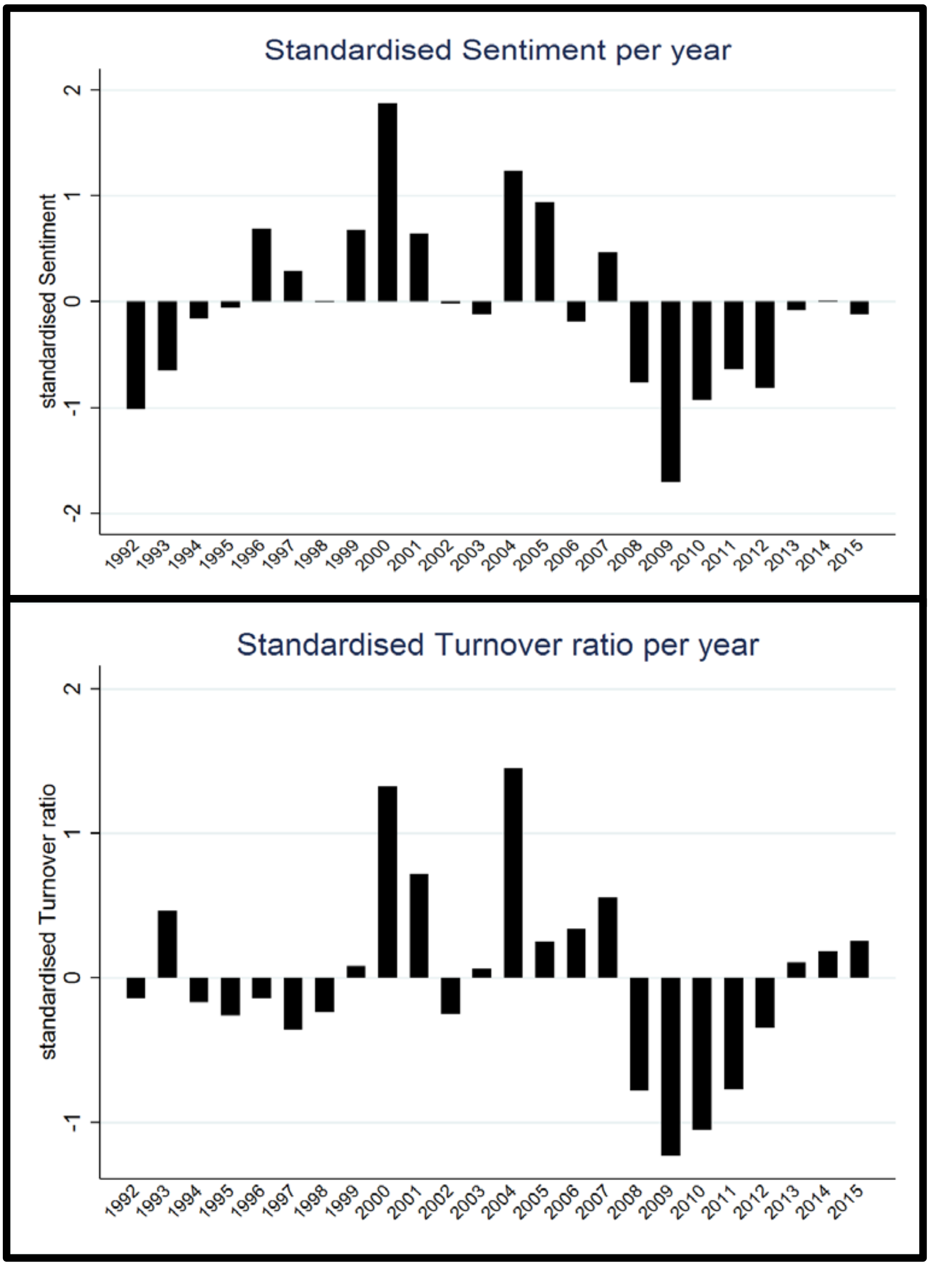
A comparison between yearly averages of FE and sentiment index from 1992 to 2015. FE is is the yearly average of forecast error. Both values are standardised. $\boldsymbol{FE_T} = \frac{\boldsymbol{F_t - E_t}}{\boldsymbol{|E_t|}}$. Where F is the earnings forecast at time t and E is the reported earnings per share at time t. Sentiment is the yearly average of monthly sentiment index estimated using the principal component analysis, based on seven sentiment components : Closed end fund discount, Forecast error, Number of IPOs, return on first day of IPOs, Turnover, Divident premium, percentage of equity issues over total equity and debt issues. The values in the figure are standardised





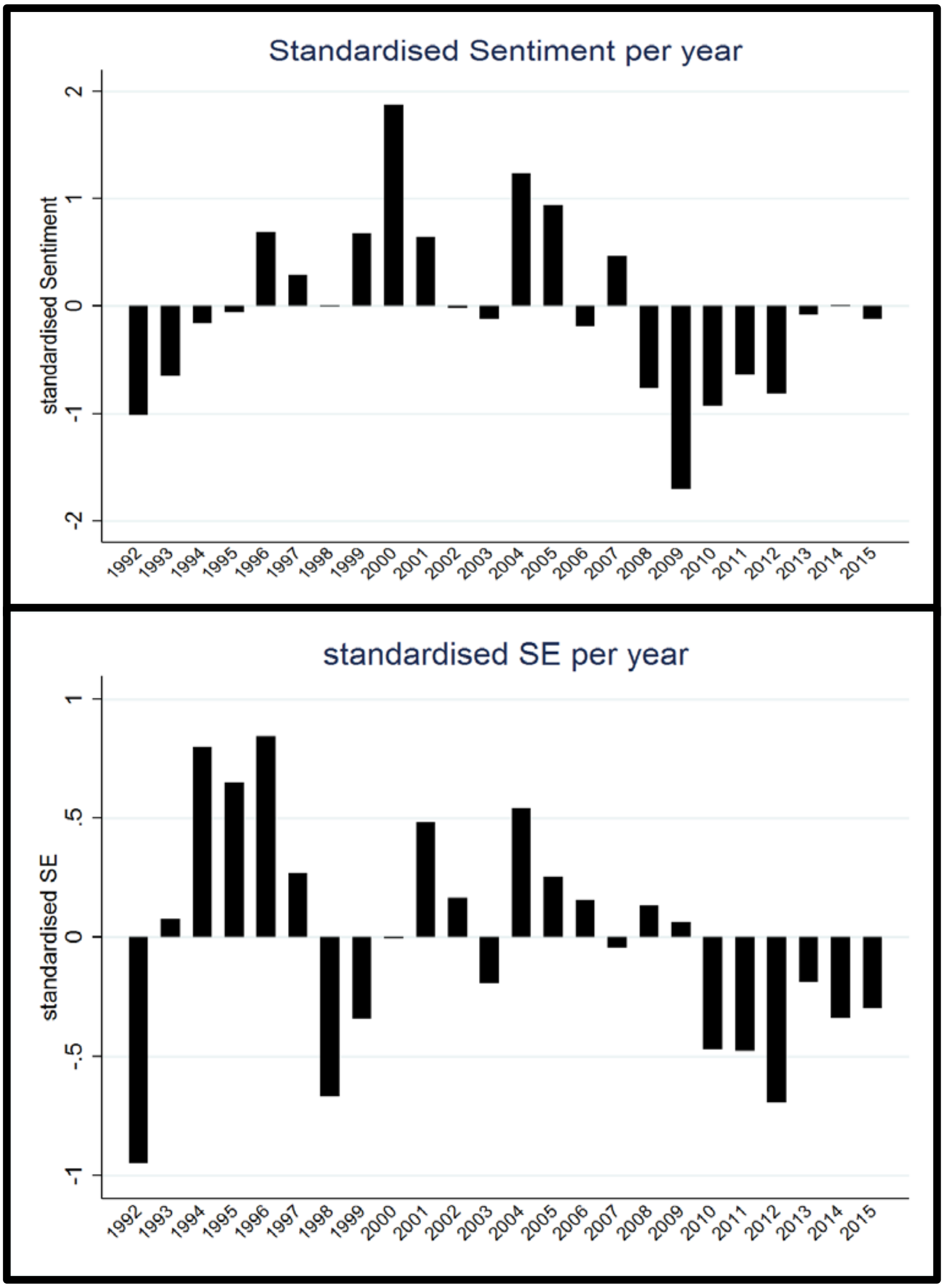
Appendix 2

A comparison between yearly averages of Turnover ratio and sentiment index from 1992 to 2015. Both values are standardised. Turnover ratio is the yearly de-trended natural log Turnover (5 years moving average) which is the ratio of reported trading volume over average shares listed in LSE. Sentiment is the yearly average of monthly sentiment index estimated using the principal component analysis, based on seven sentiment components : Closed end fund discount, Forecast error, Number of IPOs, return on first day of IPOs, Turnover, Divident premium, percentage of equity issues over total equity and debt issues. The values in the figure are standardised



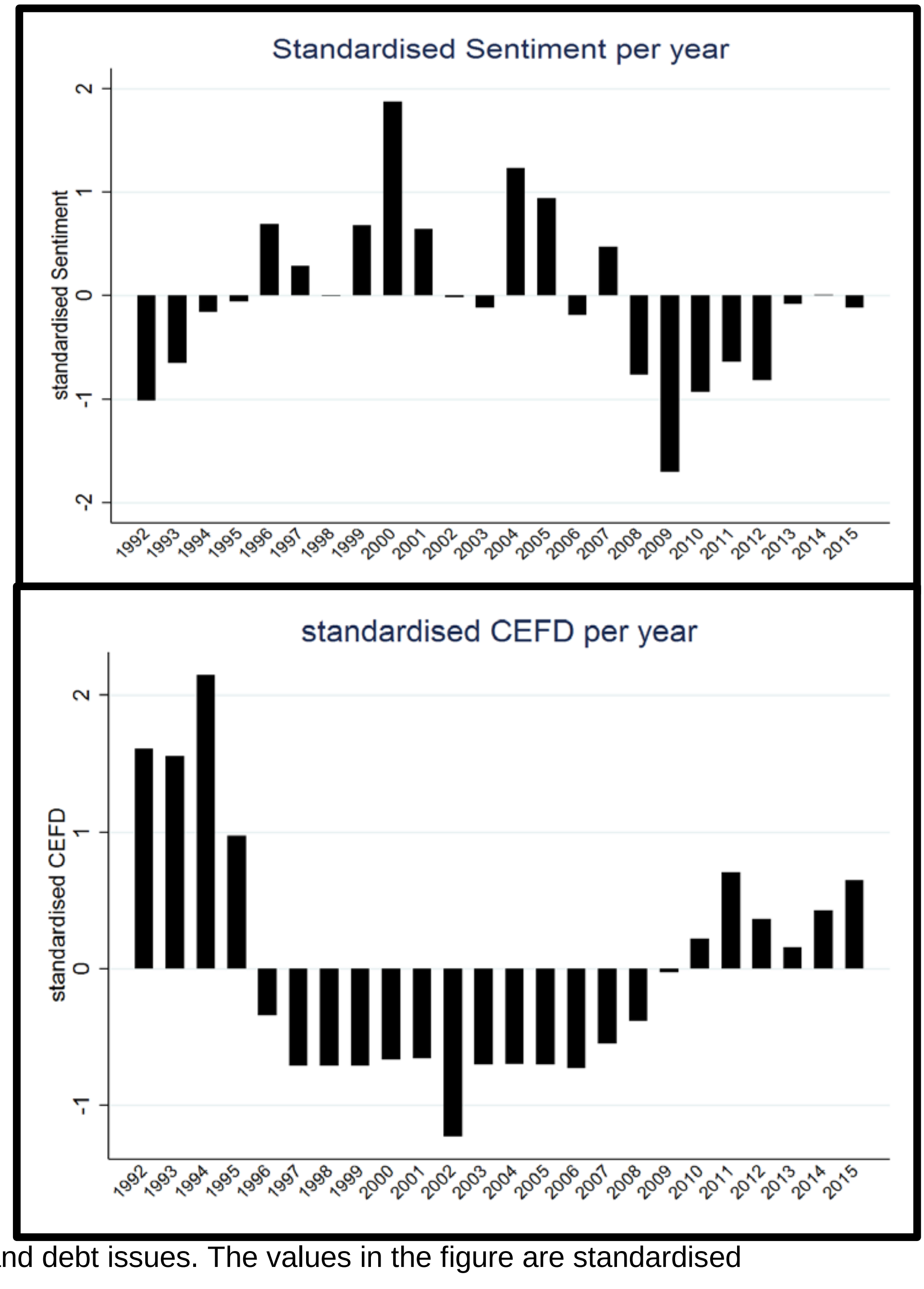
Appendix 3

A comparison between yearly averages of SE and sentiment index from 1992 to 2015. Both values are standardised. SE_t is the yearly average of share of monthly equity issuance to total equity and debt issuance. Sentiment is the yearly average of monthly sentiment index estimated using the principal component analysis, based on seven sentiment components : Closed end fund discount, Forecast error, Number of IPOs, return on first day of IPOs, Turnover, Divident premium, percentage of equity issues over total equity and debt issues. The values in the figure are standardised



Appendix 4

A comparison between yearly averages of CEFD and sentiment index from 1992 to 2015. Both values are standardised. $CEFD_t$ is the yearly average of monthly values of discount on closed-end mutual funds. Sentiment is the yearly average of monthly sentiment index estimated using the principal component analysis, based on seven sentiment components : Closed end fund discount, Forecast error, Number of IPOs, return on first day of IPOs, Turnover, Divident premium, percentage of equity issues over total equity



and debt issues. The values in the figure are standardised

Appendix 5

Average monthly percent of returns for portfolios formed on lag Sentiment and size, lag Sentiment and BTM ratio (Book to market); from January 1992 until December 1995 (288 months). Where Months are sorted into three groups of Sentiment which is the sentiment index at the end of the previous fiscal year, including Forecast Error as a seventh proxy (using 33% and 66% as the break-point percentiles). B is book value of equity at the end of fiscal year ending in year t-1 and M is market cap at the end of fiscal year t-1. Size is the Market capitalisation. Stocks are sorted according to the BTM quintiles from low to high, and according to size quintiles from small to big. The combination of BTM and lag Sentiment groups produces 18 value weighted portfolios. The same thing applies to size with Sentiment. SMB is small minus big. HML is high minus low BTM.

Panel A: Size

Sentiment*	small	2	3	4	big	SMB	average
low	-1.91423	-0.34435	0.98744	1.3586	1.18691	-3.10114	0.254874
neutral	-2.49782	-0.92283	0.21894	0.54752	0.23652	-2.73434	-0.48353
high	-1.9646	-0.30097	0.41134	1.39762	1.47516	-3.43976	0.20371
Difference	-0.05037	0.04338	-0.5761	0.03902	0.28825		

Panel B: Book-to-market quintiles

Sentiment*	Low	2	3	4	high	HML	average
low	1.07255	0.95171	1.34977	0.9623	1.81751	-0.74496	1.230768
neutral	0.18433	-0.04307	-0.05713	0.24003	1.55507	-1.37074	0.375846
high	1.24779	1.56699	1.45022	1.89372	1.60494	-0.35715	1.552732
Difference	0.17524	0.61528	0.10045	0.93142	-0.21257		

Appendix 6

Average monthly percent of returns for portfolios formed on lag Sentiment and Investment ratio; lag Sentiment and profitability, from January 1992 until December 1995 (288 months). Where Months are sorted into three groups of Sentiment which is the sentiment index at the end of the previous fiscal year, including Forecast Error as a seventh proxy (using 33% and 66% as the break-point percentiles). Investment is the percentage change in total assets between the end of fiscal year t-1 and t-2. Profitability is the operating profitability divided by book equity. Stocks are sorted according to the Investment quintiles from conservative to aggressive. The combination of investment and lag Sentiment groups produces 18 value weighted portfolios. The same thing applies to profitability with Sentiment. CMA is conservative minus aggressive investing. RMW is robust minus weak profitability.

Panel A: Investment quintiles

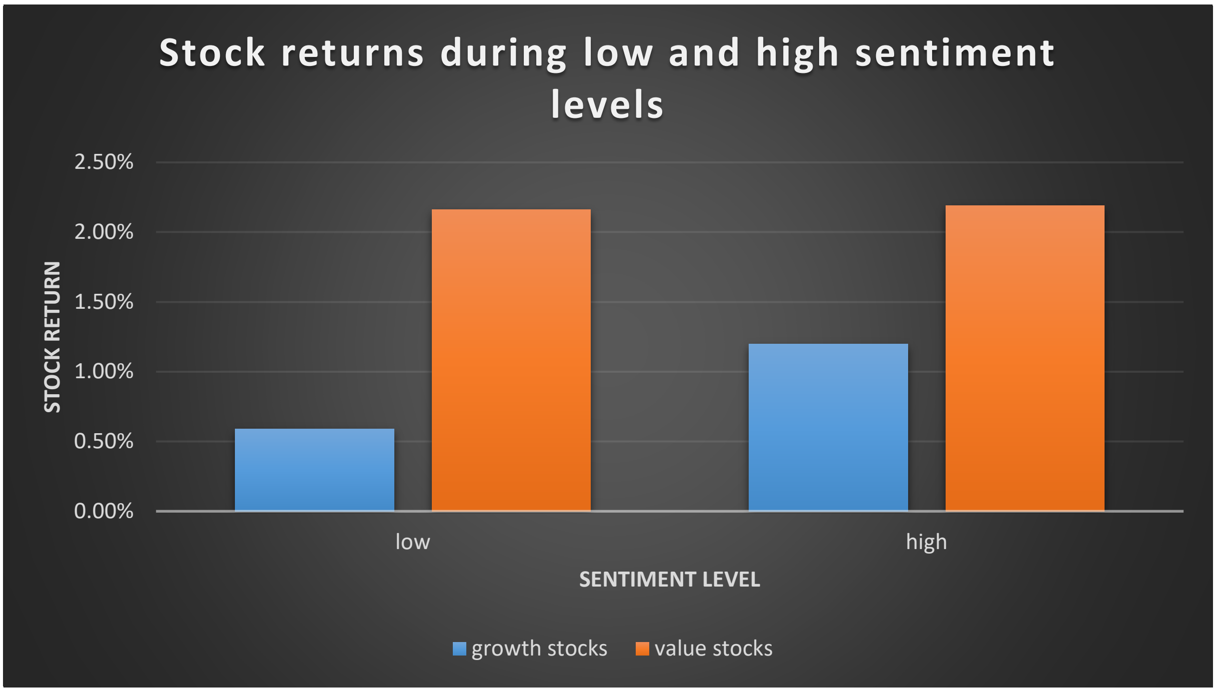
Sentiment*	Conservative	2	3	4	Aggressive	CMA	average
low	1.47334	1.1684	0.79475	0.99802	2.39939	-0.92605	1.36678
neutral	-0.0754	0.2981	0.27842	0.18063	0.42597	-0.50137	0.221544
high	1.35973	1.43967	1.68102	1.5676	0.90034	0.45939	1.389672
Difference	-0.11361	0.27127	0.88627	0.56958	-1.49905		

Panel B: Profitability quintiles

Sentiment*	weak	2	3	4	robust	RMW	average
low	1.44183	0.45705	0.88343	1.40357	1.39606	0.04577	1.116388
neutral	-1.21568	-0.05598	0.4628	-0.0472	0.50588	-1.72156	-0.07004
high	-0.23627	0.74375	1.06464	1.62821	1.94633	-2.1826	1.029332
Difference	-1.6781	0.2867	0.18121	0.22464	0.55027		

Appendix 7

Stock Returns during low and high Sentiment levels, for growth and value stocks according to BTM quintiles; where Sentiment is the index estimated using principal component analysis with proxies as detailed in chapter 4. The sample starts from January 1992 until December 1995 (288 months). B is book value of equity at the end of fiscal year ending in year t-1 and M is market cap at the end of fiscal year t-1. Months are sorted into three groups of Sentiment level which is the sentiment index at the last fiscal year (using 33% and 66% as the break-point percentiles).



Appendix 8

Regression analysis of actual change on forecast change at different horizons after controlling for the FCA applying the ***Transparency Directive requirements set by the European commission in December 2004***. Regression analysis showing Analyst Forecast Bias from 11 to 1 month prior to earnings announcement date, including yearly average and yearly weighted average. Original regression results are shown in addition to results after deleting forecast errors which are greater than 200% (considered as outliers). $\boldsymbol{AC_{it}} = \boldsymbol{\alpha_i} + \boldsymbol{\beta_1}\ \boldsymbol{FC_{iht}} + \boldsymbol{\beta_2}\ \boldsymbol{D_t} + \boldsymbol{\varepsilon_{it}}$. *Where AC_{it} is the actual change in EPS from t-1 to t; FC_{iht}, the forecast change (outliers are trimmed at 200%), measures the deviation of the forecast in year t at horizon h from the previous earnings per share; D is the dummy variable of 1 if the year falls after 2004 and 0 before.*

horizons per month	**B_1 (t-statistics)**	**α (t-statistics)**	**n. observations**	**R-squared**
11	0.791*** (11.67)	-0.0938*** (-4.646)	3,557	0.565
10	0.881*** (12.50)	-0.116*** (-5.398)	3,568	0.661
9	0.895*** (13.36)	-0.119*** (-5.988)	3,587	0.668
8	0.913*** (13.50)	-0.114*** (-5.877)	3,593	0.677
7	0.807*** (10.24)	-0.0876*** (-3.889)	3,601	0.676
6	0.815*** (10.06)	-0.0850*** (-3.708)	3,623	0.666
5	0.804*** (11.17)	-0.0779*** (-3.874)	3,615	0.710
4	0.784*** (11.55)	-0.0712*** (-3.919)	3,605	0.731
3	0.785*** (12.35)	-0.0663*** (-4.018)	3,593	0.766
2	0.771*** (11.96)	-0.0587*** (-3.586)	3,559	0.770
1	0.823*** (18.43)	-0.0683*** (-6.120)	3,534	0.777
Average	0.915*** (15.05)	-0.111*** (-6.724)	3,556	0.728
weighted average	0.893*** (16.55)	-0.101*** (-6.987)	3,538	0.753
t-stat in parentheses	*** p<0.01, ** p<0.05, * p<0.1			